
An

Multigrid Tutorial

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AMG:

What **is** Algebraic Multigrid??

- Any multilevel method where geometry is not used (and may not be available) to build coarse grids, interpolation and restriction, or coarse-grid operators.
- “Classical” AMG was introduced by Brandt, McCormick and Ruge in 1982. It was explored early on by Stueben in 1983, and popularized by Ruge and Stuben in 1987.
- This tutorial will describe only the classical AMG algorithm.

AMG:

What **is** Algebraic Multigrid??

- Many other algorithms qualify under the definition given. Some whose approaches are closely related to “classical AMG”:
 - Chang
 - Griebel, Neunhoefffer, Regler
 - Huang
 - Krechel, Stueben
 - Zaslavsky
- Work close to the original, but using different approaches to coarsening or interpolation:
 - Fuhrmann
 - Kicking

AMG:

What **is** Algebraic Multigrid??

- **Other approaches that are important, novel, historical, or weird:**
 - Multigraph methods (Bank & Smith)
 - Aggregation methods (Braess; Chan & Zikatanov & Xu)
 - Smoothed Aggregation methods (Mandel & Brezina & Vanek)
 - Black Box Multigrid (Dendy, Dendy & Bandy)
 - Algebraic Multilevel Recursive Solver (Saad)
 - Element based algebraic multigrid (Chartier; Cleary et al)
 - MultiCoarse correction with Suboptimal Operators (Sokol)
 - Multilevel block ILU methods (Jang & Saad; Bank & Smith & Wagner; Reusken)
 - AMG based on Element Agglomeration (Jones & Vassilevski)
 - Sparse Approximate Inverse Smoothers (Tang & Wan)
 - Algebraic Schur- Complement approaches (Axelsson & Vassilevski & Neytcheva)

Highlights of Multigrid: The 1-d Model Problem

- Poisson's equation: $-u'' = f$ in $[0,1]$, with boundary conditions $u(0) = u(1) = 0$.

- Discretized as:

$$\frac{-u_{i-1} + 2u_i - u_{i+1}}{h^2} = f_i \quad u_0 = u_N = 0$$

- Leads to the Matrix equation $Au = f$, where

$$A = \frac{1}{h^2} \begin{pmatrix} 2 & -1 & & & \\ -1 & 2 & -1 & & \\ & -1 & 2 & -1 & \\ & & & \ddots & \ddots \\ & & & -1 & 2 & -1 \\ & & & & -1 & 2 \end{pmatrix}, \quad u = \begin{pmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_{N-2} \\ u_{N-1} \end{pmatrix}, \quad f = \begin{pmatrix} f_1 \\ f_2 \\ f_3 \\ \vdots \\ f_{N-2} \\ f_{N-1} \end{pmatrix}$$

Highlights of Multigrid: Weighted Jacobi Relaxation

- Consider the iteration:

$$u_i^{(new)} = (1 - \omega) u_i^{(old)} + \frac{\omega}{2h^2} (u_{i-1}^{(old)} + u_{i+1}^{(old)} + f_i)$$

- Letting $A = D+L+U$, the matrix form is:

$$\begin{aligned} u^{(new)} &= \left[(1 - \omega)I - \omega D^{-1}(L + U) \right] u^{(old)} + \omega D^{-1}f \\ &= G u^{(old)} + \omega D^{-1}f \end{aligned}$$

- It is easy to see that if $e = u^{(exact)} - u^{(approx)}$, then

$$e^{(new)} = G e^{(old)}$$

Highlights of Multigrid: Relaxation Typically Stalls

- The eigenvectors of G are the same as those of A , and are Fourier Modes: $v_i = \sin(ik\pi/N)$, $k = 1, 2, \dots, N-1$

- The eigenvalues of G are $1 - 2 \sin^2(k\pi/2N)$, so the effect of relaxation on the modes is:

$$N = 400$$

$$= 1/3$$

$$= 1/2$$

$$= 2/3$$

$$= 1$$

Note: No value of ω will damp out the low frequency waves

Highlights of Multigrid:

Relaxation Smooths the Error

- Initial error,
- Error after 35 iteration sweeps:

Many relaxation schemes have the smoothing property, where oscillatory modes of the error are eliminated effectively, but smooth modes are damped very slowly.

Highlights of Multigrid: Smooth error can be represented on a coarse grid

- A smooth function:
- Can be represented by linear interpolation from a coarser grid:

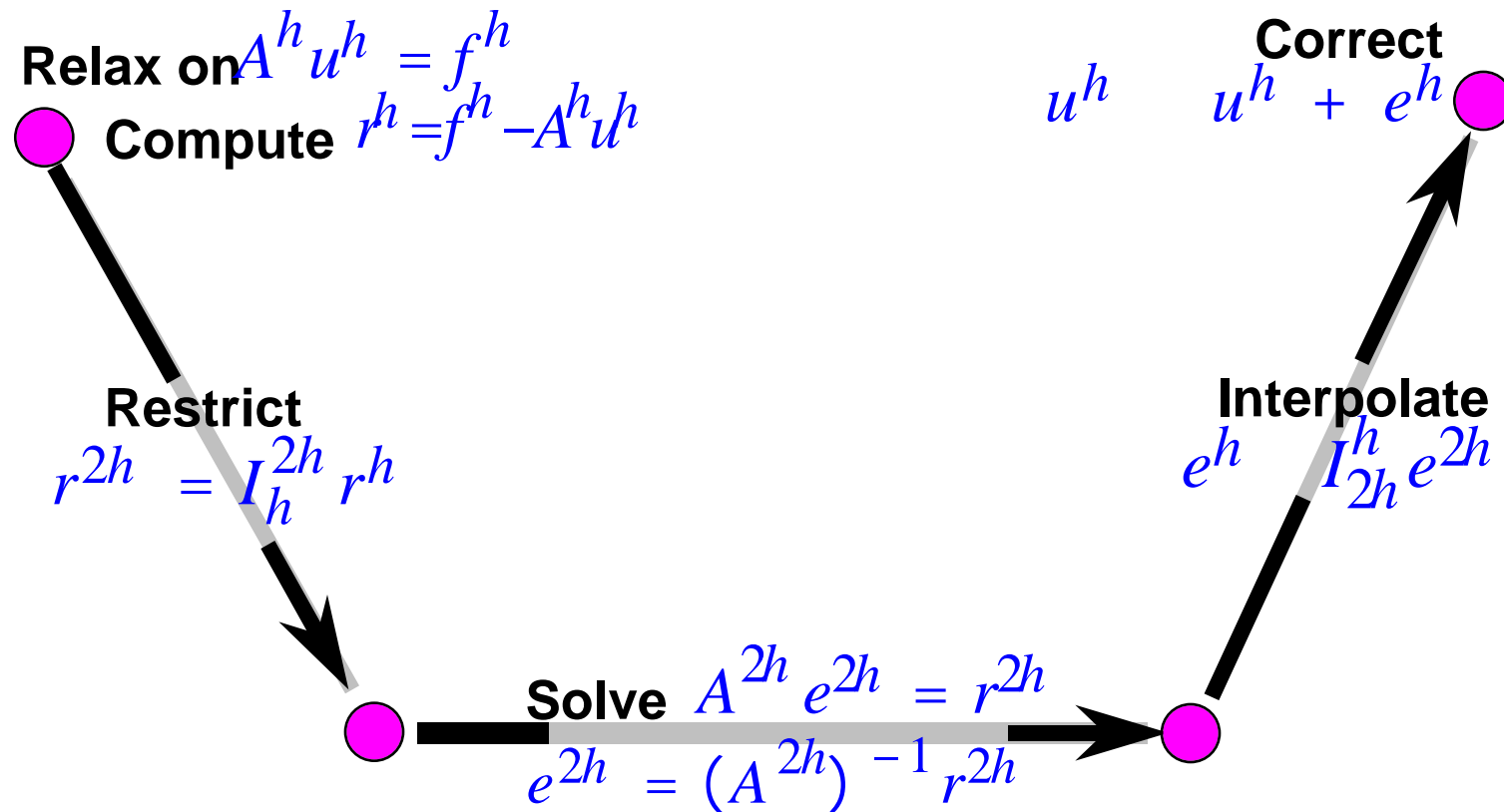
On the coarse grid, the smooth error appears to be relatively higher in frequency: in the example it is the 4- mode, out of a possible 16, on the fine grid, $1/4$ the way up the spectrum. On the coarse grid, it is the 4- mode out of a possible 8, hence it is $1/2$ the way up the spectrum.

Relaxation will be more effective on this mode if done on the coarser grid!!

Highlights of Multigrid: Coarse-grid Correction

- Perform relaxation on $A^h u^h = f^h$ on fine grid until error is smooth.
- Compute residual, $r^h = f^h - A^h u^h$ and transfer to the coarse grid $r^{2h} = I_h^{2h} r^h$.
- Solve the coarse-grid residual equation to obtain the error: $A^{2h} e^{2h} = r^{2h}$, $e^{2h} = (A^{2h})^{-1} r^{2h}$
- Interpolate the error to the fine grid and correct the fine-grid solution: $u^h \leftarrow u^h + I_{2h}^h e^{2h}$

Highlights of Multigrid: Coarse-grid Correction



Highlights of Multigrid: Tools Needed

- Interpolation and restriction operators:

$$I_{2h}^h = \begin{matrix} & 0.5 & & \\ & 1.0 & & \\ 0.5 & 0.5 & & \\ & 1.0 & & \\ & 0.5 & 0.5 & \\ & & 1.0 & \\ & & 0.5 & \end{matrix}, \quad I_h^{2h} = \begin{matrix} & 0 & 1 & 0 \\ & & 0 & 1 & 0 \\ & & & 0 & 1 & 0 \end{matrix}, \quad I_h^{2h} = \begin{matrix} & 0.25 & 1.0 & 0.25 \\ & & 0.25 & 1.0 & 0.25 \\ & & & 0.25 & 1.0 & 0.25 \end{matrix}$$

Linear

Injection

Full-weighting

Interpolation

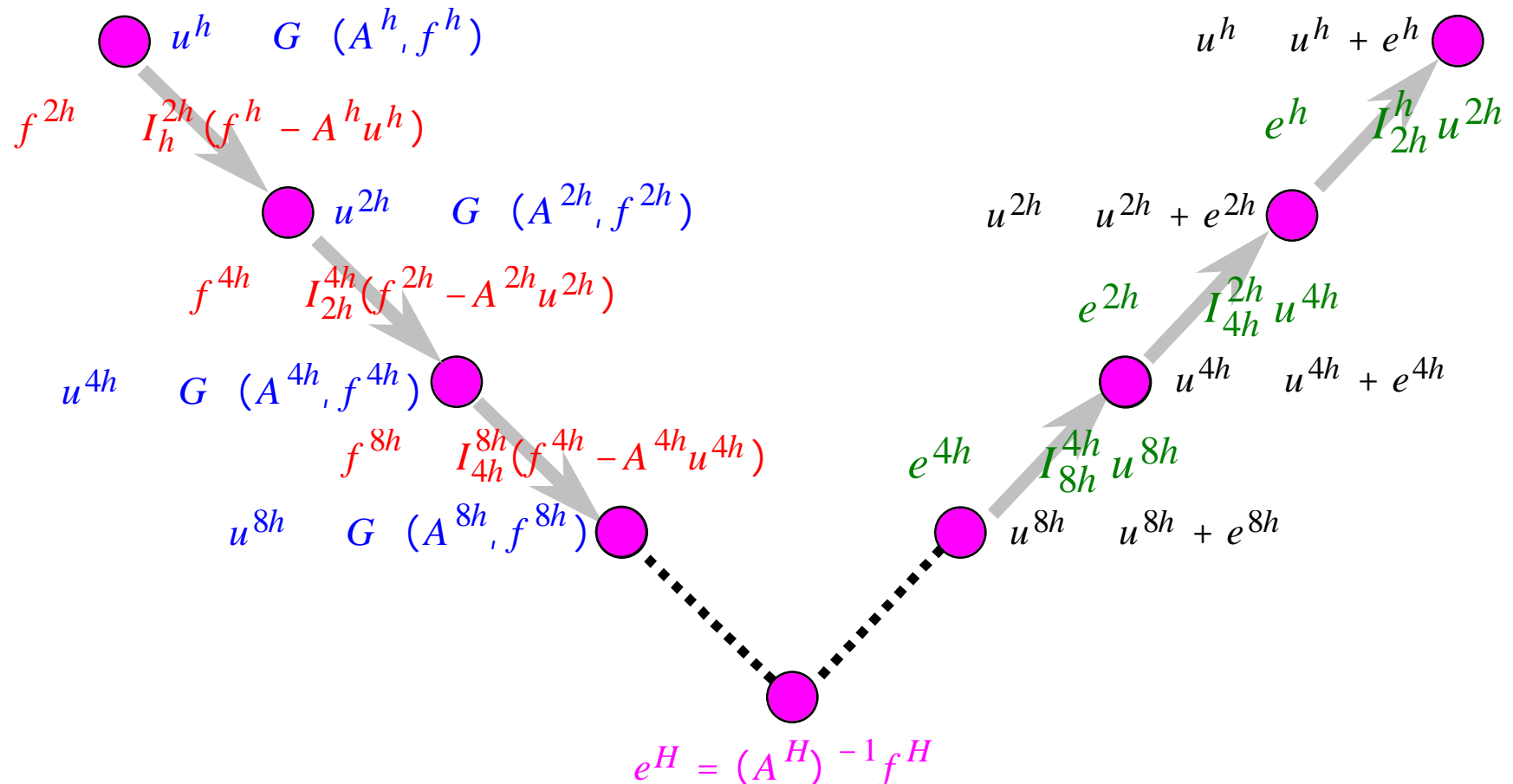
- Coarse-grid Operator A^{2h} . Two methods:
(1) Discretize equation at larger spacing
(2) Use Galerkin Formula:

$$A^{2h} = I_h^{2h} A^h I_{2h}^h$$

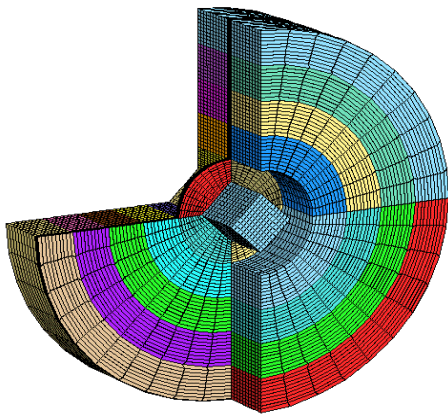
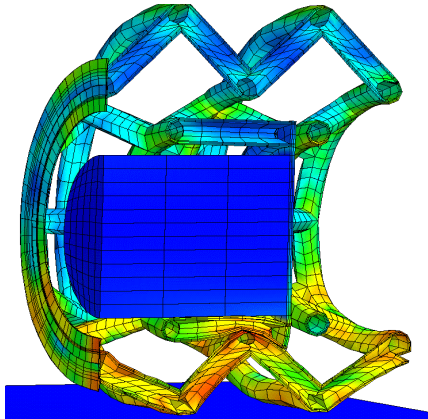
Highlights of Multigrid:

Recursion: the $(\cdot, 0)$ V-cycle

- Major question: How do we “solve” the coarse-grid residual equation? **Answer: recursion!**



Algebraic multigrid: for unstructured- grids



- Automatically defines coarse “grid”
 - AMG has two distinct phases:
 - **setup phase: define MG components**
 - solution phase: perform MG cycles
 - AMG approach is opposite of geometric MG
 - fix relaxation (point Gauss- Seidel)
 - choose coarse “grids” and prolongation, P , so that error not reduced by relaxation is in $range(P)$
 - define other MG components so that coarse- grid correction eliminates error in $range(P)$ (i. e., use Galerkin principle)
- (in contrast, geometric MG fixes coarse grids, then defines suitable operators and smoothers)

AMG has two phases:

- **Setup Phase**

- Select Coarse “grids,” $m + 1, m = 1, 2, \dots$

- Define **interpolation**, $I_{m+1}^m, m = 1, 2, \dots$

- Define **restriction** and **coarse-grid operators**

$$I_m^{m+1} = (I_{m+1}^m)^T \quad A^{m+1} = I_m^{m+1} A^m I_{m+1}^m$$

- **Solve Phase**

- Standard multigrid operations, e.g., V-cycle, W-cycle, FMG, etc

In AMG, we choose relaxation first:

- Typically, pointwise Gauss-Seidel is used

$$A = (D + L + U)$$

- The iteration is developed:

$$Ax = b$$

$$(D + L)x = b - Ux$$

$$x^{new} = (D + L)^{-1}b - (D + L)^{-1}Ux^{old}$$

- Add and subtract $(D + L)^{-1}(D + L)x^{old}$ to get:

$$x^{new} = x^{old} + (D + L)^{-1}r^{old}$$

Gauss- Seidel relaxation error propagation:

- The iteration is:

$$x^{new} = x^{old} + (D + L)^{-1} r^{old}$$

- Subtracting both sides from the exact solution:

$$x^{exact} - x^{new} = x^{exact} - (x^{old} + (D + L)^{-1} r^{old})$$

$$e^{new} = e^{old} - (D + L)^{-1} r^{old}$$

- Using $r = A e$ this can be written as:

$$e^{new} = \left[I - (D + L)^{-1} A \right] e^{old}$$

An observation: **error that is slow to converge** ? “small” residuals

- Consider the iterative method error recurrence

$$e^{k+1} = (I - Q^{-1}A) e^k$$

- Error that is slow to converge satisfies

$$\begin{aligned} (I - Q^{-1}A) e &= e - Q^{-1}A e = 0 \\ &? \quad r = 0 \end{aligned}$$

- Perhaps a better viewpoint is

$$(I - Q^{-1}A) e = e - Q^{-1}A e \quad ? \quad \langle Q^{-1}A e, A e \rangle \ll \langle e, A e \rangle$$

Some implications of slow convergence

- For most iterations (e.g., Jacobi or Gauss-Seidel) this last holds if $\langle D^{-1}Ae, Ae \rangle \ll \langle e, Ae \rangle$. (1)

- Hence $\sum_{i=1}^N \frac{r_i^2}{a_{ii}} \ll \sum_{i=1}^N r_i e_i$ implying that, **on average**,

$$|r_i| \ll a_{ii} |e_i|$$

- An implication is that, if e is an error slow to converge, then locally at least, e_i can be well-approximated by an average of its neighbors:

In **Multigrid**, error that is slow to converge is **geometrically smooth**

- Combining the algebraic property that slow convergence implies “small residuals” with the observation above, in AMG we DEFINE smooth error:
- Smooth error is that error which is slow to converge under relaxation, that is,

$$(I - Q^{-1}A) e \quad e$$

or, more precisely,

$$\|(I - Q^{-1}A) e\|_A \quad \|e\|_A$$

But sometimes, smooth error **isn't!** (example from Klaus Stueben)

- Consider the problem

$$-(a u_x)_x - (b u_y)_y + c u_{xy} = f(x, y)$$

- on the unit square, using a regular Cartesian grid, with finite difference stencils and values for **a, b, and c**:

a=1 b=1000 c=0	A=1 b=1 c=2
a=1 b=1 c=0	a=1000 b=1 c=0

$$u_{xx} = h^{-2} \begin{bmatrix} 1 & -2 & 1 \end{bmatrix}$$

$$u_{yy} = \frac{1}{h^2} \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}$$

$$u_{xy} = \frac{1}{2h^2} \begin{bmatrix} -1 & 1 \\ 1 & -2 & 1 \\ 1 & -1 \end{bmatrix}$$

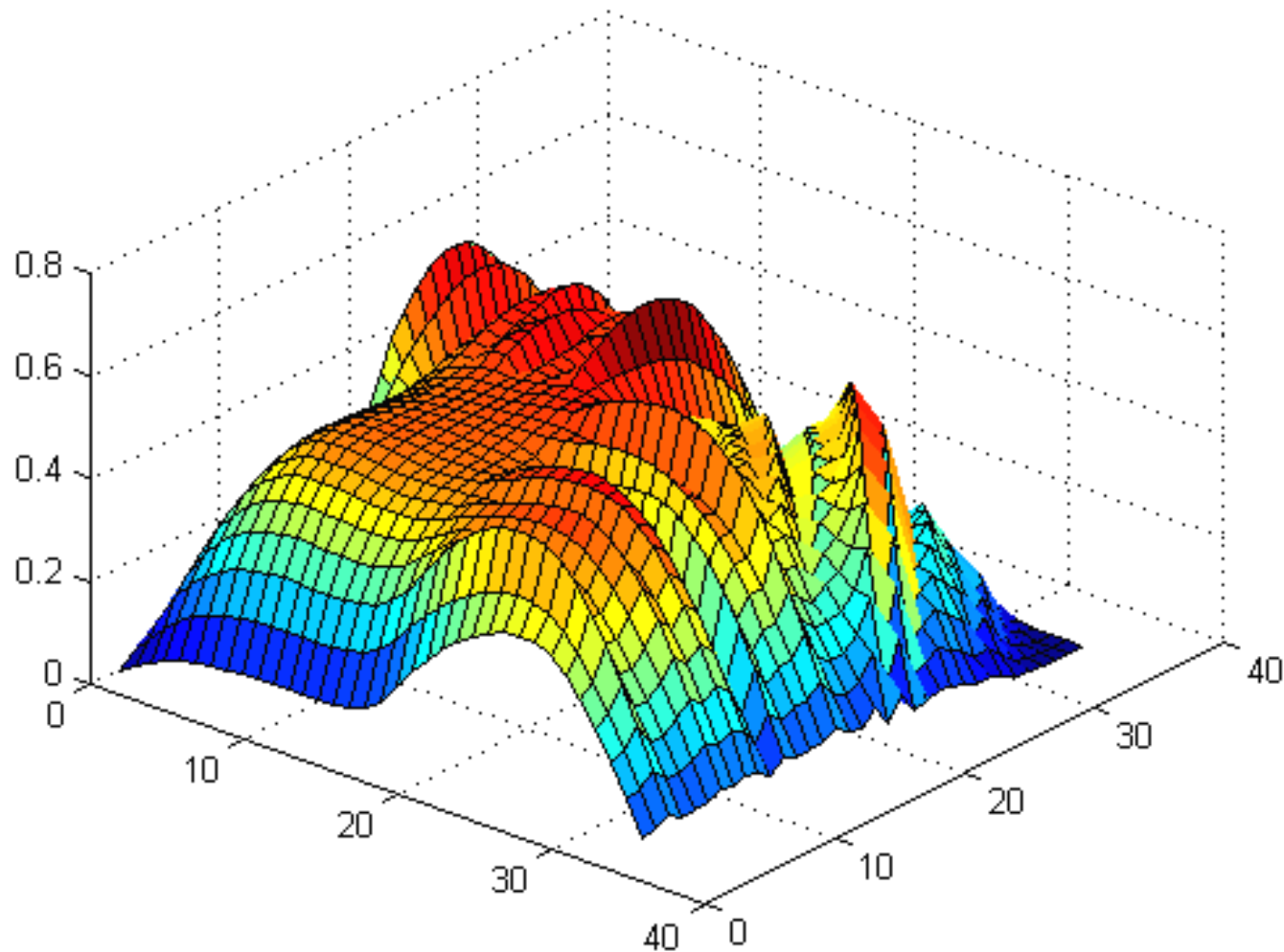
But sometimes, smooth error isn't!

$$-(a u_x)_x - (b u_y)_y + c u_{xy} = f(x, y)$$

- Using a zero right-hand side and a random initial guess, after 8 sweeps of Gauss-Seidel iteration the error is unchanging in norm. By our definition, the error is smooth. And it looks like this:

Smooth error for

$$-(a u_x)_x - (b u_y)_y + c u_{xy} = f(x, y)$$



AMG uses **dependence (influence)** to determine MG components

- We need to choose a subset of the gridpoints (coarse grid) that can be used **1)** to represent smooth errors, and **2)** to interpolate these errors to the fine grid.
- Intuitively, a point u_j is a good candidate for a **C-point** if its value is important in determining the value of another point, u_i in the **ith** equation.
- If the a_{ij} coefficient is “large” compared to the other off-diagonal coefficients in the **ith** equation then u_j **influences** u_i (or u_i **depends on** u_j).

Dependence and smooth error

- For M-matrices, we define “*i depends on j*” by

$$-a_{ij} \leq \max_{k \neq i} \{-a_{ik}\}, \quad 0 < \alpha < 1$$

alternatively, “*j influences i*.”

- It is easy to show from (1) that smooth error satisfies $\langle Ae, e \rangle \ll \langle De, e \rangle$ (2)

Dependence and smooth error

- For M-matrices, we have from (2)

$$\frac{1}{2} \frac{-a_{ij}}{a_{ii}} \frac{e_i - e_j}{e_i}^2 \ll 1$$

- If e_i does **not** depend on e_j then the inequality may be satisfied because a_{ij} is “small”.
- If e_i does depend on e_j , then a_{ij} need not be small, and the inequality must be satisfied by
- This implies that **smooth error varies slowly in the direction of dependence.**

Some useful definitions

- The set of **dependencies** of a variable u_i , that is, the variables upon whose values the value of u_i depends, is defined as

$$S_i = \{ j : -a_{ij} > \max_{k \neq i} \{ -a_{ik} \} \}$$

- The set of points that u_i **influences** is denoted:

$$S_i^T = \{ j : i \in S_j \}$$

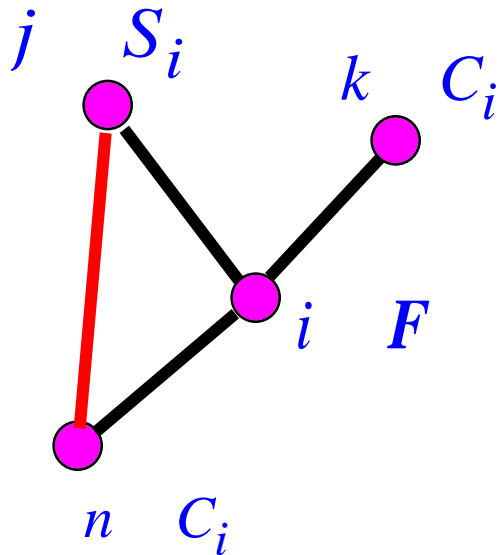
More useful definitions

- The set of coarse-grid variables is denoted C .
- The set of fine-grid variables is denoted F .
- The set of coarse-grid variables used to interpolate the value of the fine-grid variable u_i , called the *coarse interpolatory set for i* , is denoted C_i .

Two Criteria for Choosing the Coarse Grid Points

- First Criterion: F - F dependence

— (C1) For each $i \in F$, each point $j \in S_i$ should either be in C_i itself or should depend on at least one point in C_i .



Since the value of u_i depends on the value of u_j , the value of u_j must be represented on the coarse-grid for good interpolation. If j isn't a C_i -point, it should depend on a point in C_i so its value is “represented” in the interpolation.

Two Criteria for Choosing the Coarse Grid Points

- Second Criterion: Maximal Subset

- (C2) C should be a maximal subset with the property that no C -point depends on another.
- (C1) tends to increase the number of C_H -points. In general, the more C -points on H , the better the h-level convergence.
- But more C -points means more work for relaxation and interpolation.
- (C2) is designed to limit the size (and work) of the coarse grid.

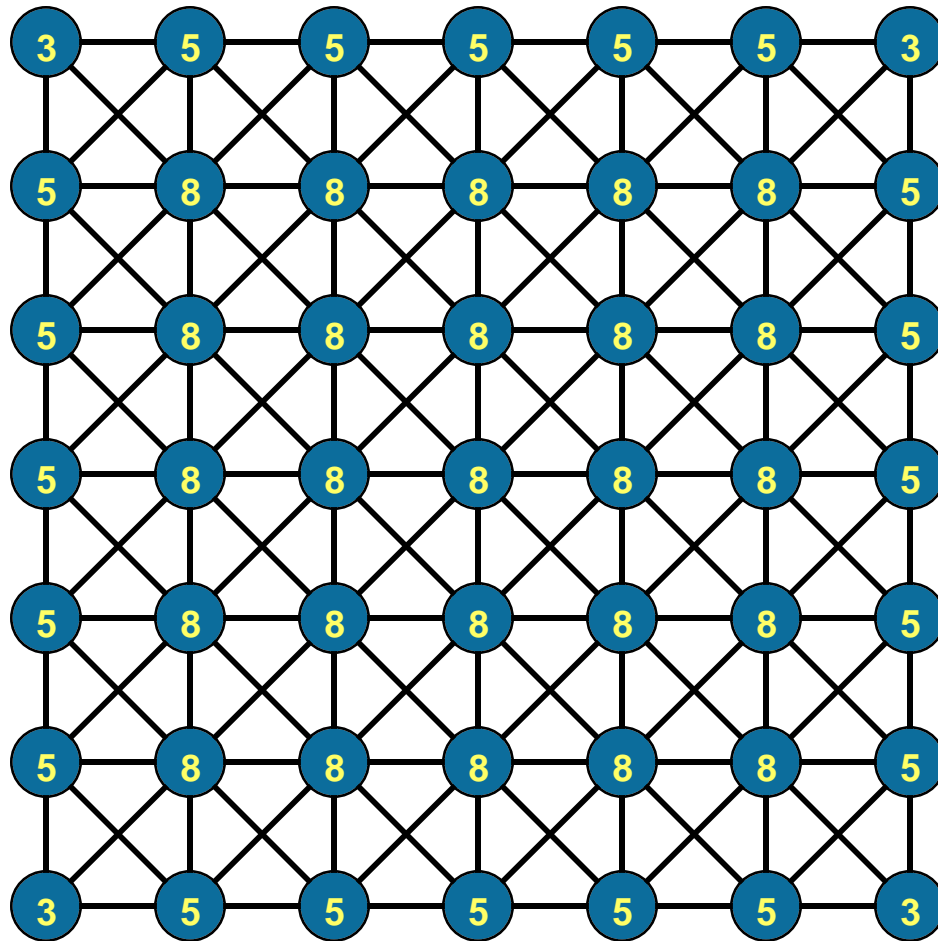
Two Criteria for Choosing the Coarse Grid Points

- It is sometimes not possible to satisfy both criteria simultaneously (an example will be seen shortly).
- In those cases, we choose to satisfy (C1), the requirement that F-F dependencies be represented in the coarse-interpolatory set, while using (C2) as a guide.
- This choice leads to somewhat larger coarse grids, but tends to preserve good convergence properties.

Choosing the Coarse Grid Points

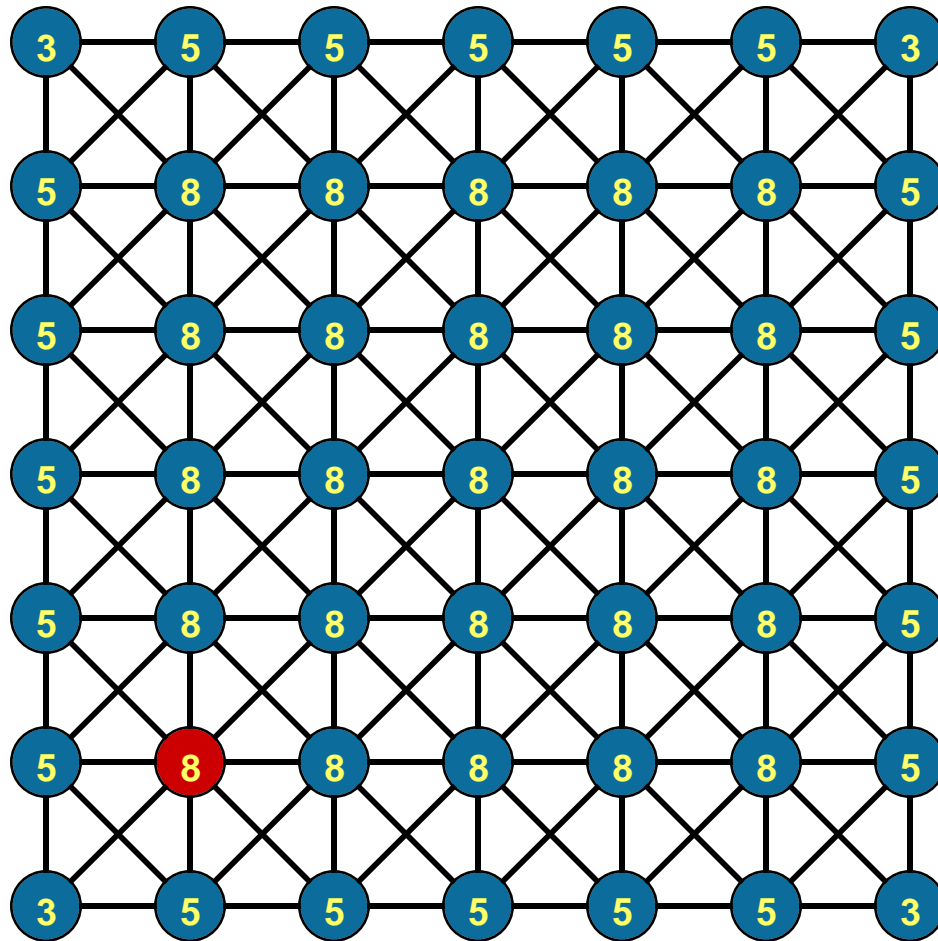
- Assign to each gridpoint k a “value” equal to the number of points that depend on k .
- Choose the first point with global maximum value as a C- point.
- The new C- point can be used to interpolate values of points it influences. Assign them all as F- points.
- Other points influencing these new F- points can be used in their interpolation. Increment their value.
- Repeat until all points are C- or F- points.

Ruge AMG: start



- select C-pt with maximal measure
- select neighbors as F-pts
- update measures of F-pt neighbors

Ruge AMG: select C-pt 1

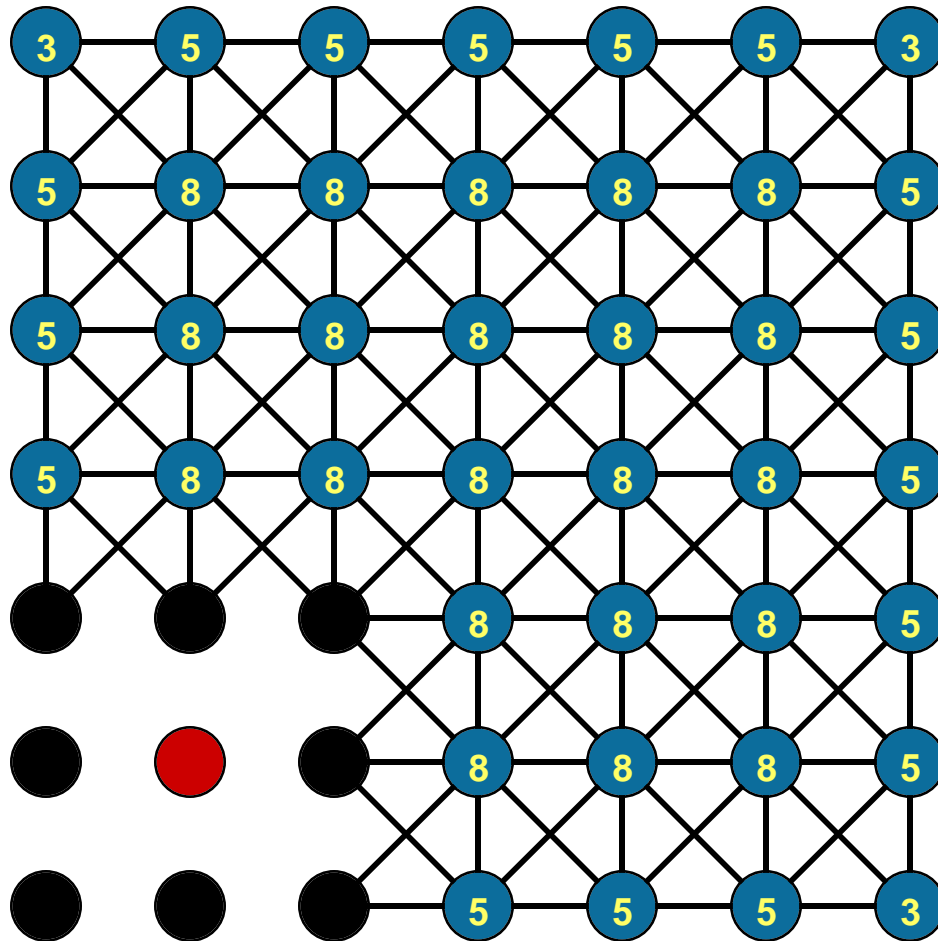


➔ **select next C-pt
with maximal
measure**

➔ **select neighbors
as F-pts**

➔ **update measures
of F-pt neighbors**

Ruge AMG: select F- pt 1

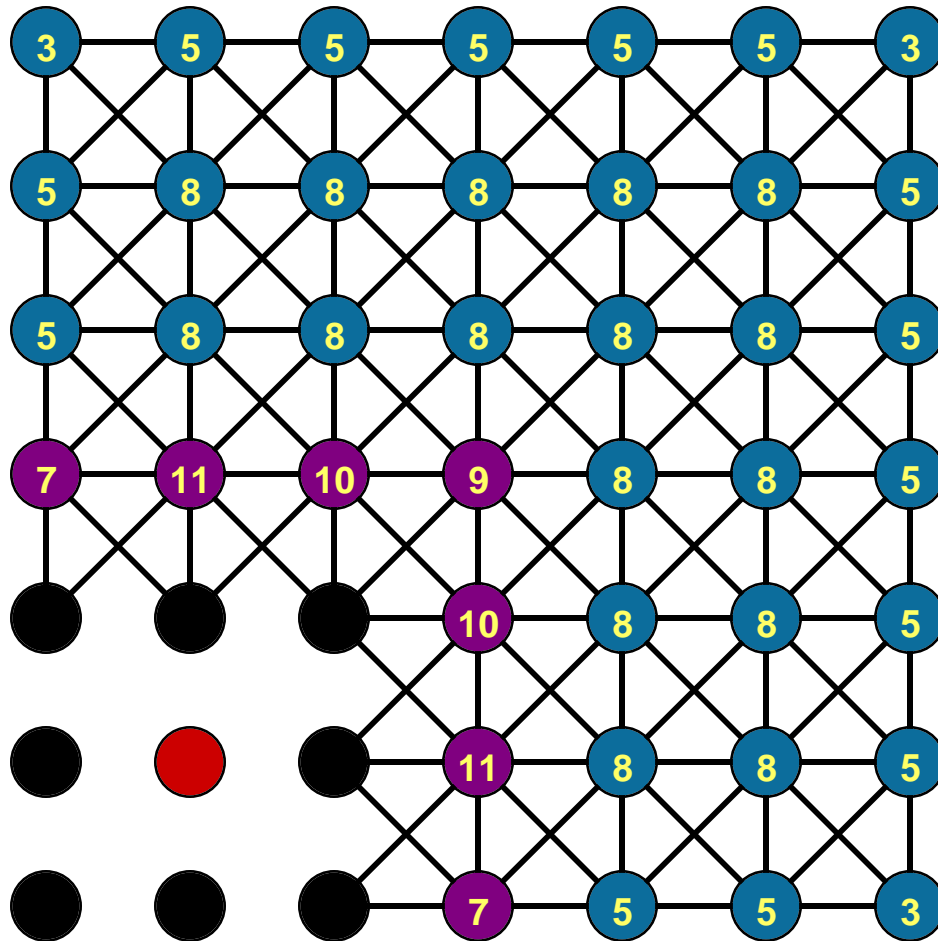


→ select C-pt with
maximal measure

→ select neighbors
as F-pts

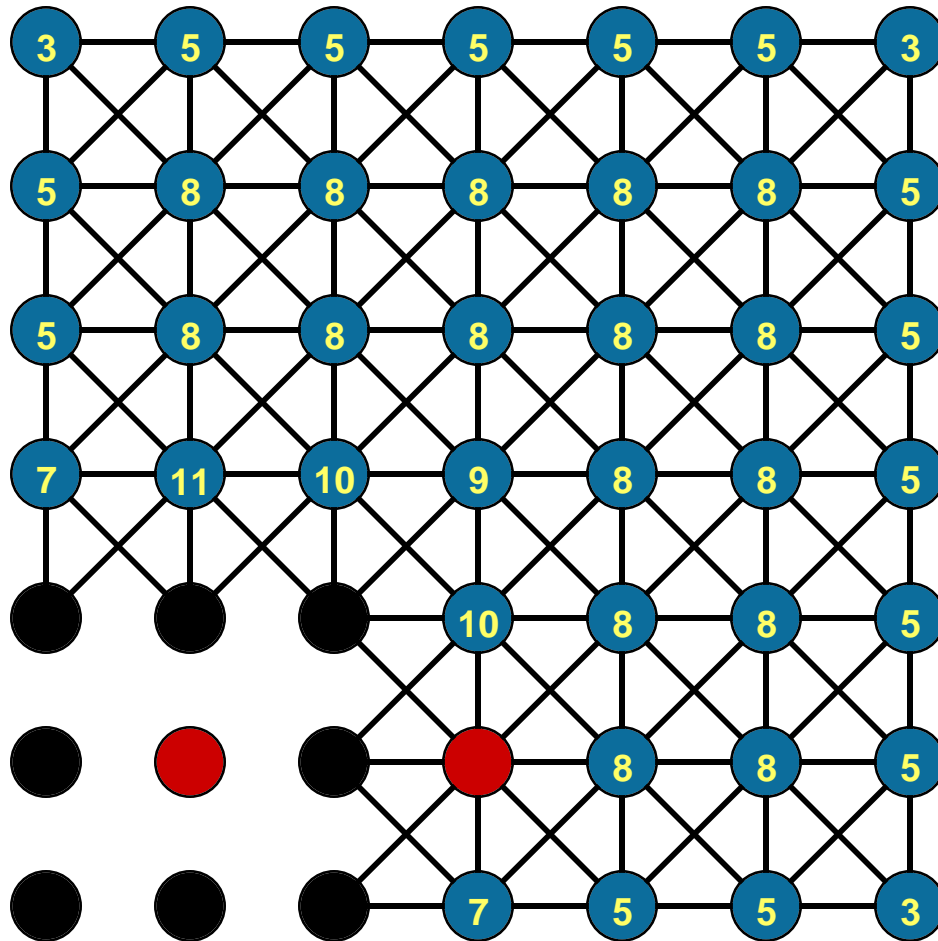
→ update measures
of F-pt neighbors

Ruge AMG: update F-pt neighbors 1



- select C-pt with maximal measure
- select neighbors as F-pts
- update measures of F-pt neighbors

Ruge AMG: select C-pt 2

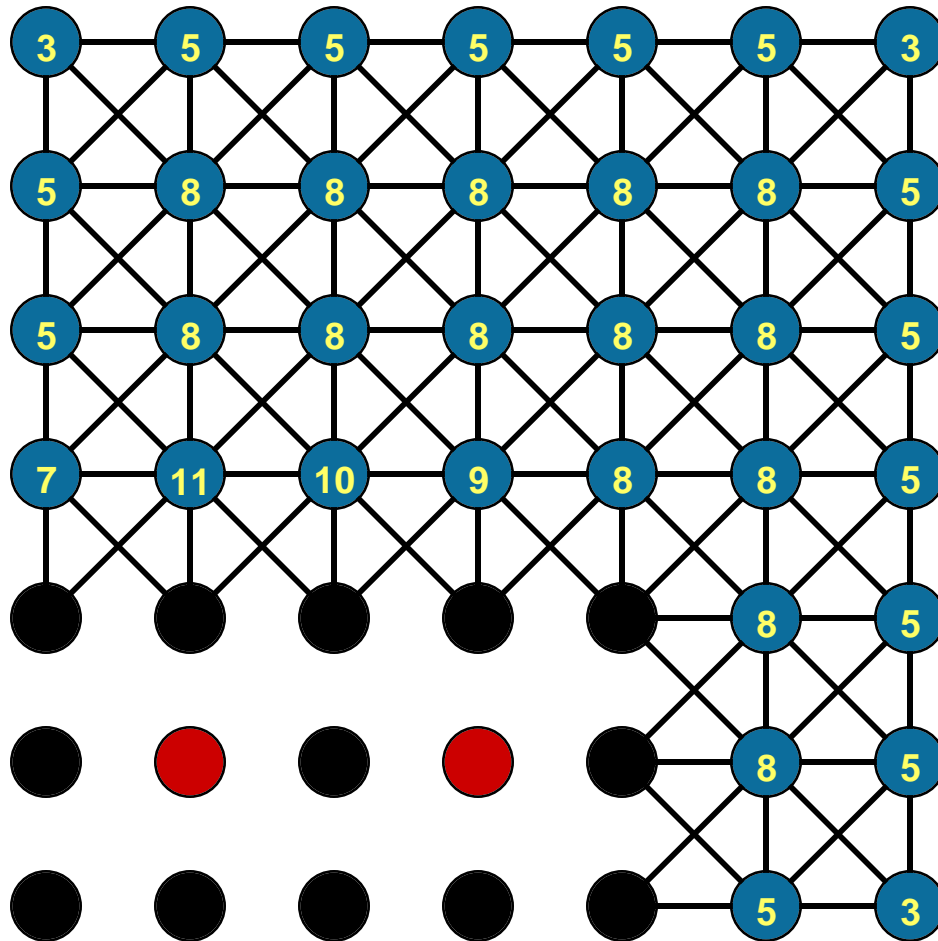


➔ **select next C-pt
with maximal
measure**

➔ **select neighbors
as F-pts**

➔ **update measures
of F-pt neighbors**

Ruge AMG: select F- pt 2

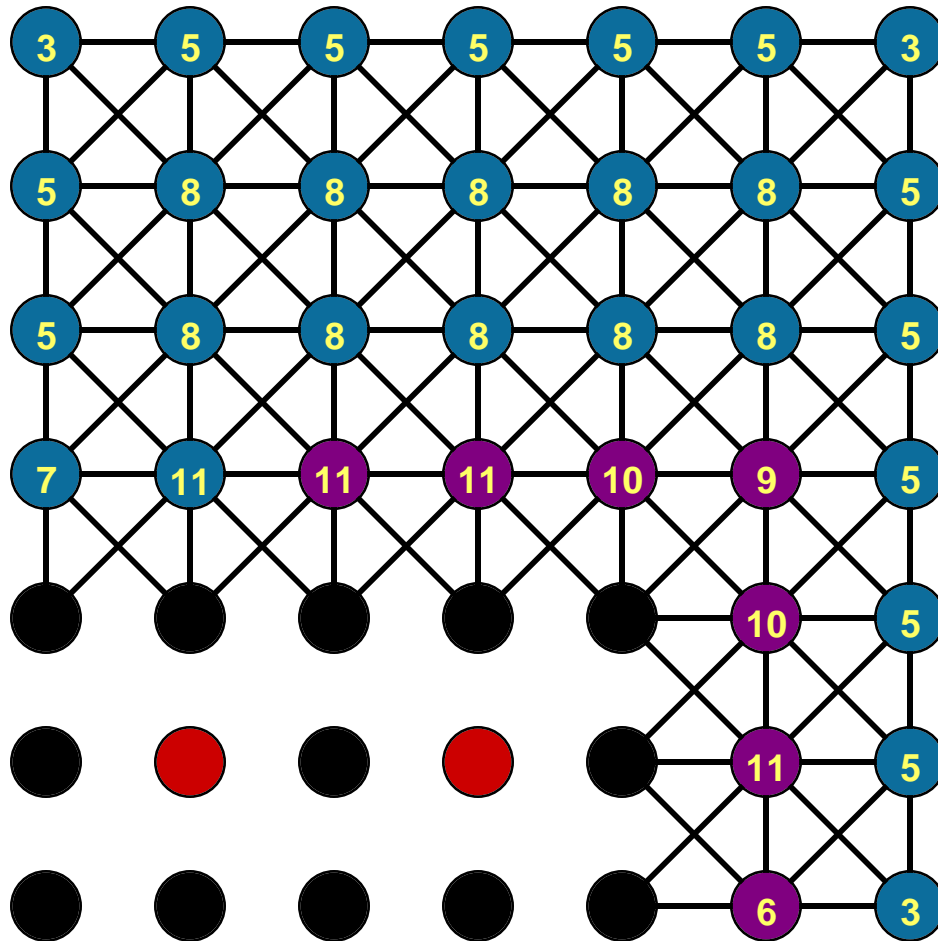


→ select next C-pt
with maximal
measure

→ select neighbors
as F-pts

→ update measures
of F-pt neighbors

Ruge AMG: update F-pt neighbors 2

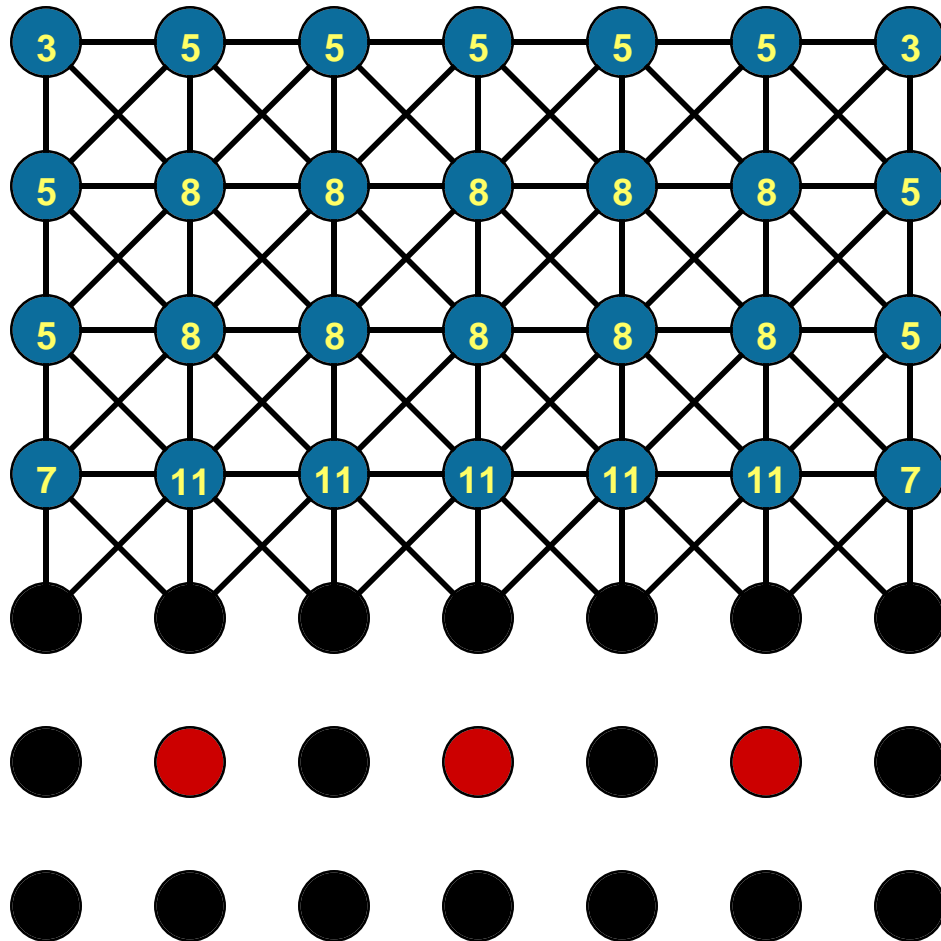


→ select next C-pt
with maximal
measure

→ select neighbors
as F-pts

→ update measures
of F-pt neighbors

Ruge AMG: select C-pt, F-pts, update neighbors 3

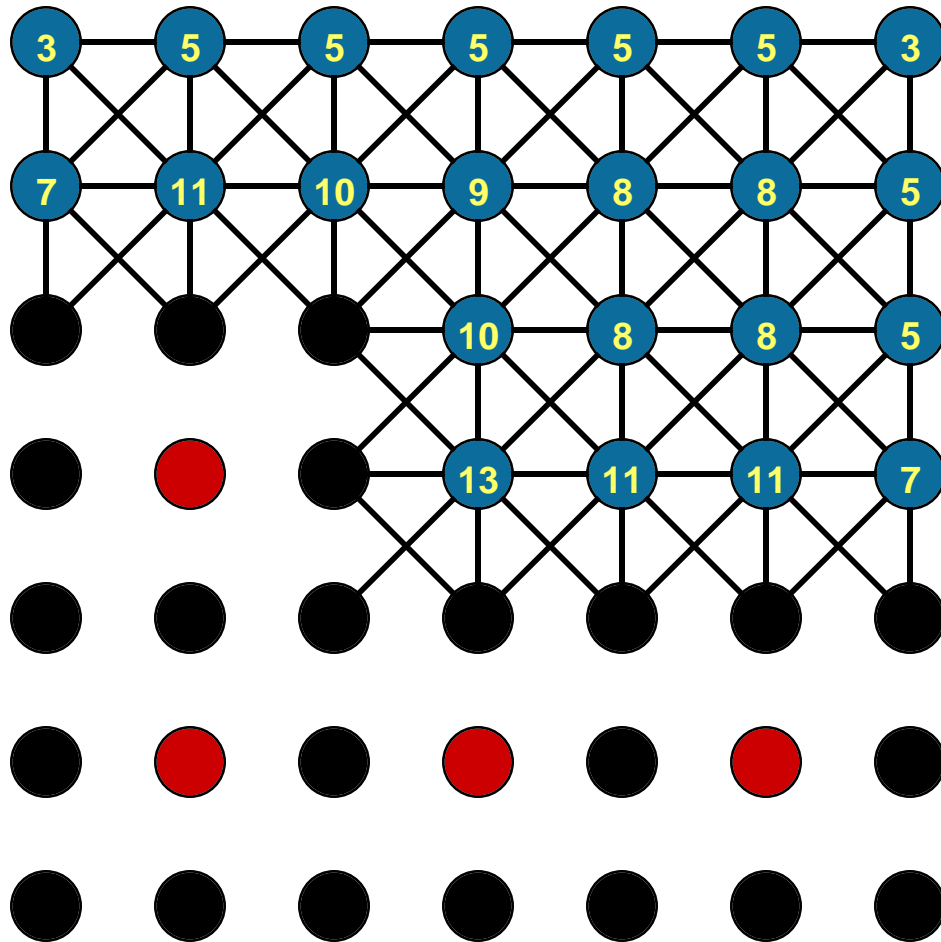


➡ select next C-pt
with maximal
measure

➡ select neighbors
as F-pts

➡ update measures
of F-pt neighbors

Ruge AMG: select C-pt, F-pts, update neighbors 4

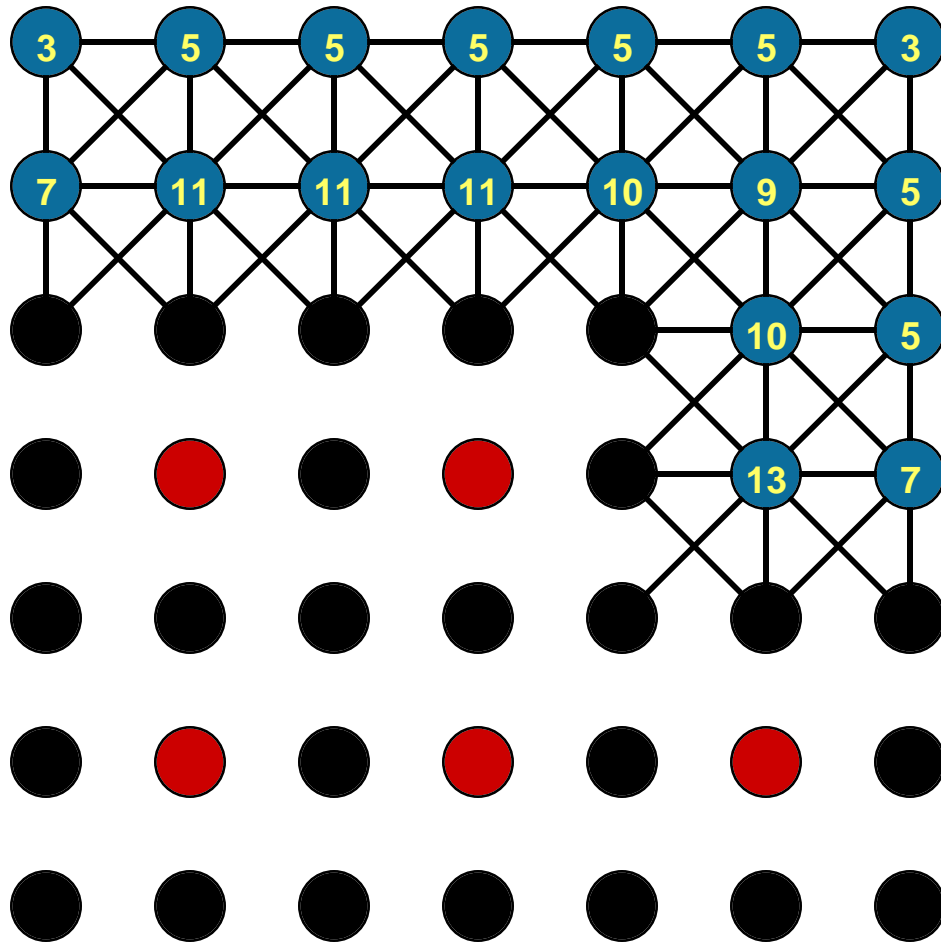


➔ select next C-pt
with maximal
measure

➔ select neighbors
as F-pts

➔ update measures
of F-pt neighbors

Ruge AMG: select C-pt, F-pts, update neighbors 5

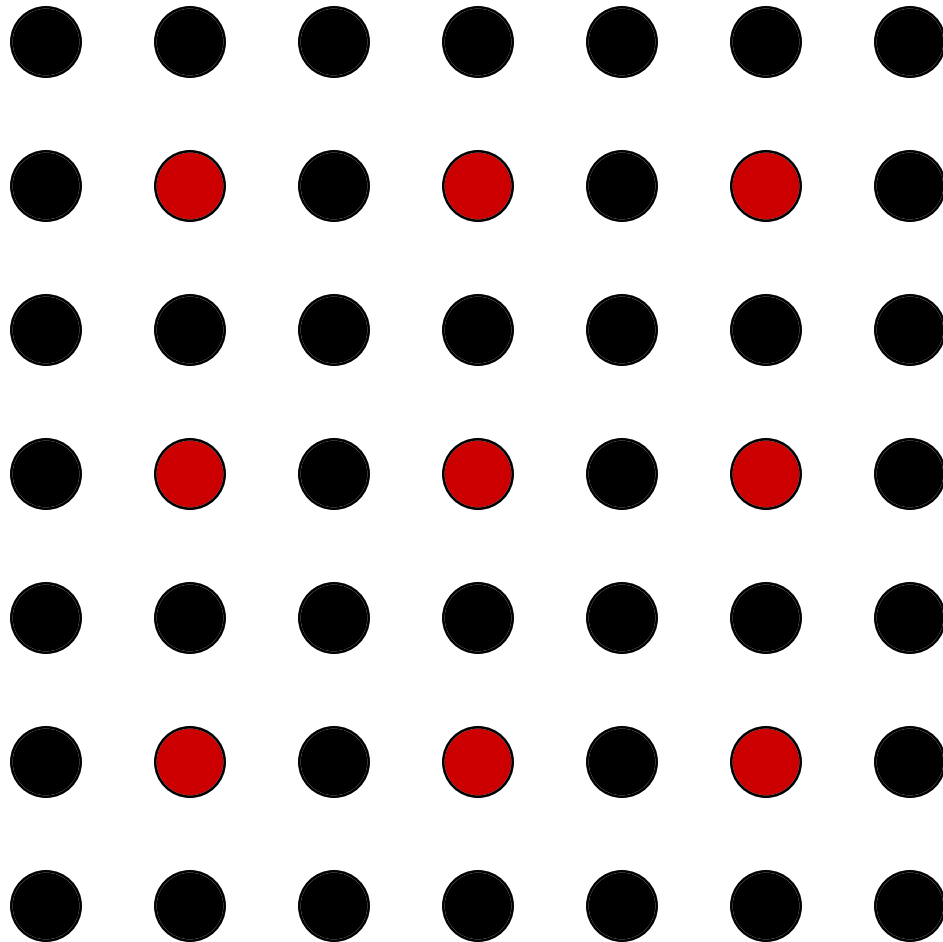


➔ select next C-pt
with maximal
measure

➔ select neighbors
as F-pts

➔ update measures
of F-pt neighbors

Ruge AMG: select C-pt, F-pts, update neighbors 6, 7, 8, 9



➔ select next C-pt
with maximal
measure

➔ select neighbors
as F-pts

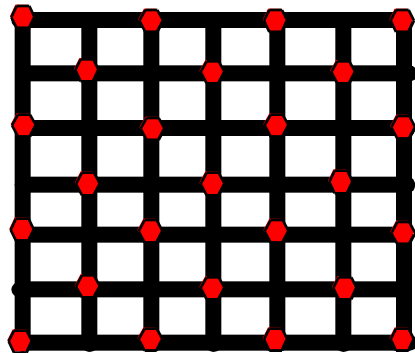
➔ update measures
of F-pt neighbors

Examples: Laplacian Operator

5-pt FD, 9-pt FE (quads), and 9-pt FE (stretched quads)

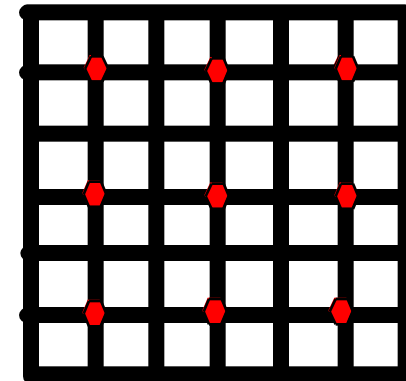
5-pt FD

$$\begin{array}{ccc} & -1 & \\ -1 & 4 & -1 \\ & -1 & \end{array}$$

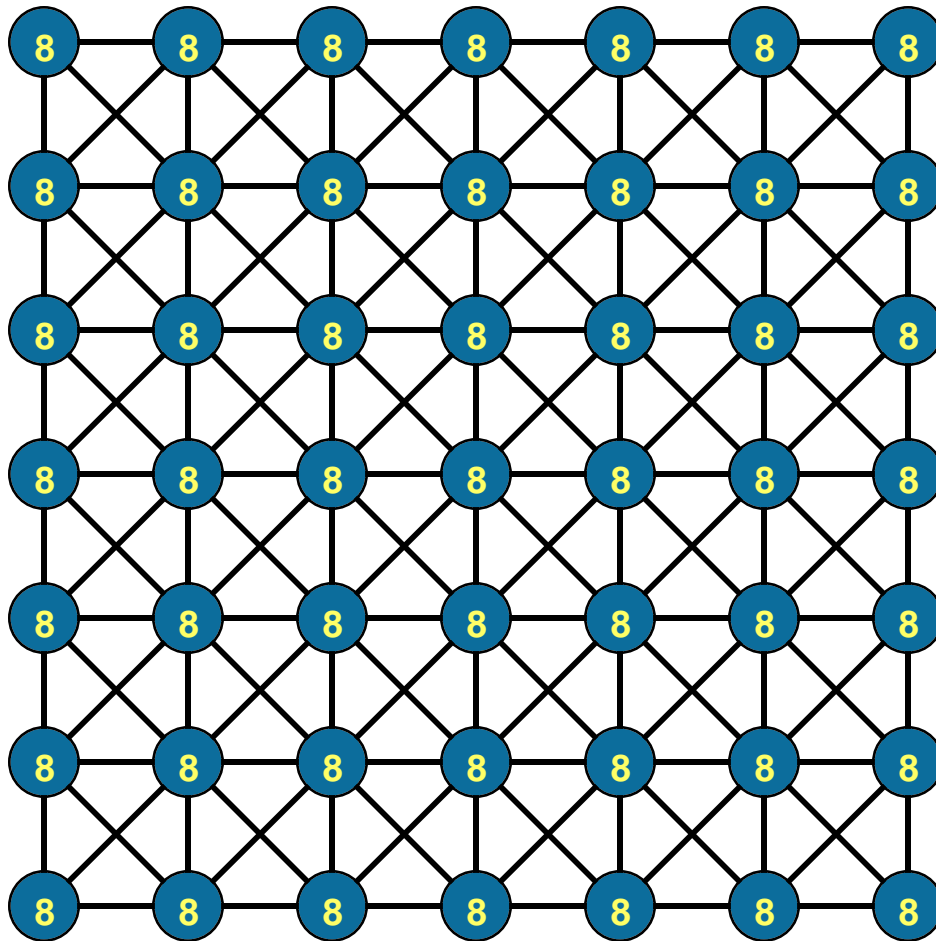


9-pt FE (quads)

$$\begin{array}{ccc} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{array}$$

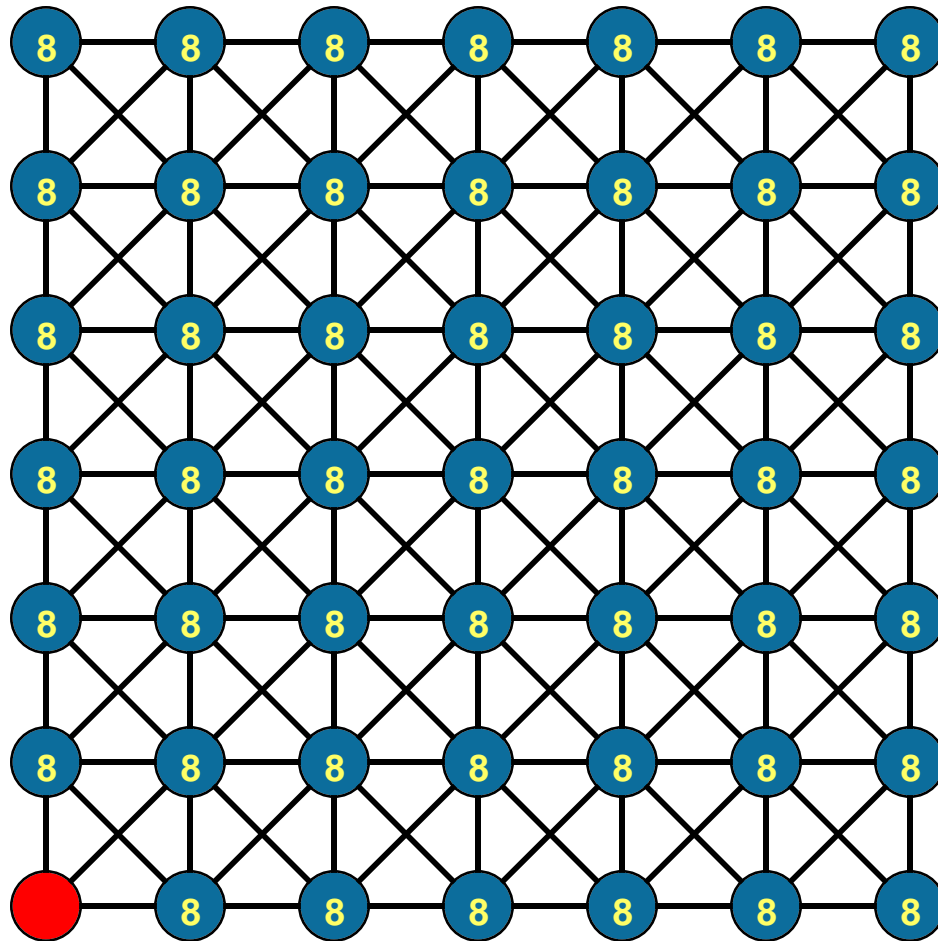


Coarse-grid selection: 9pt Laplacian, **periodic** boundary conditions



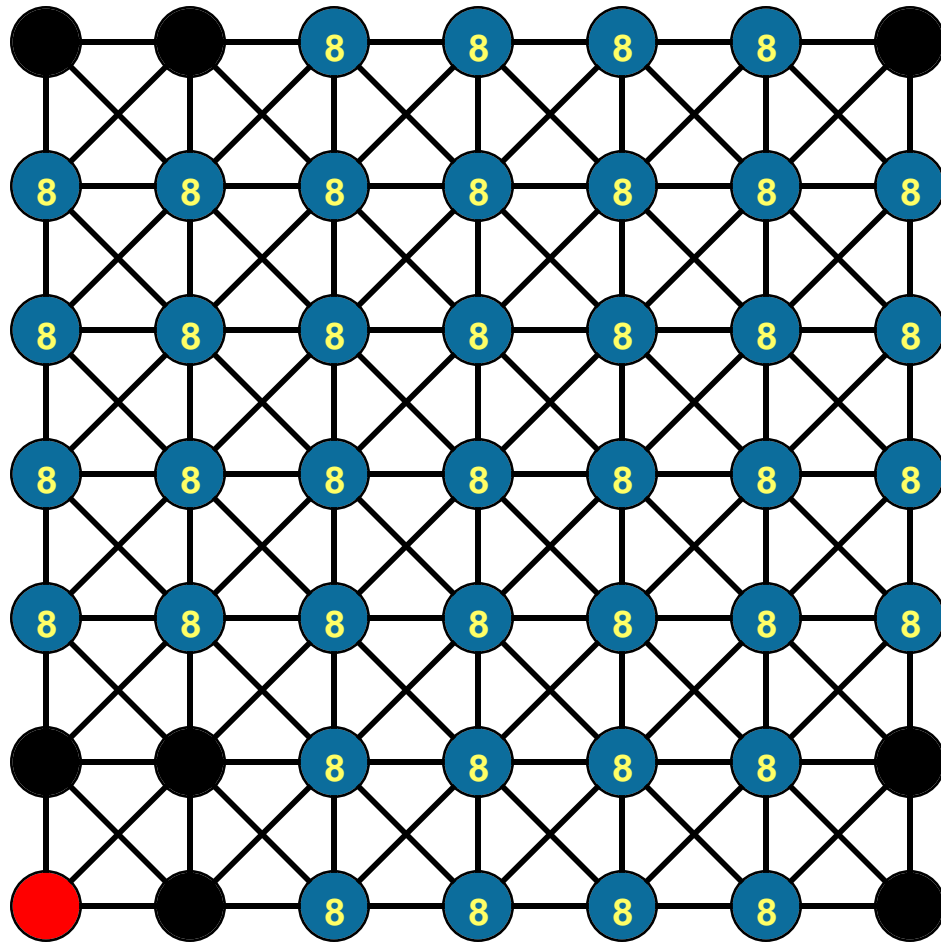
- select C-pt with maximal measure
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Coarse-grid selection: 9pt Laplacian, **periodic** boundary conditions



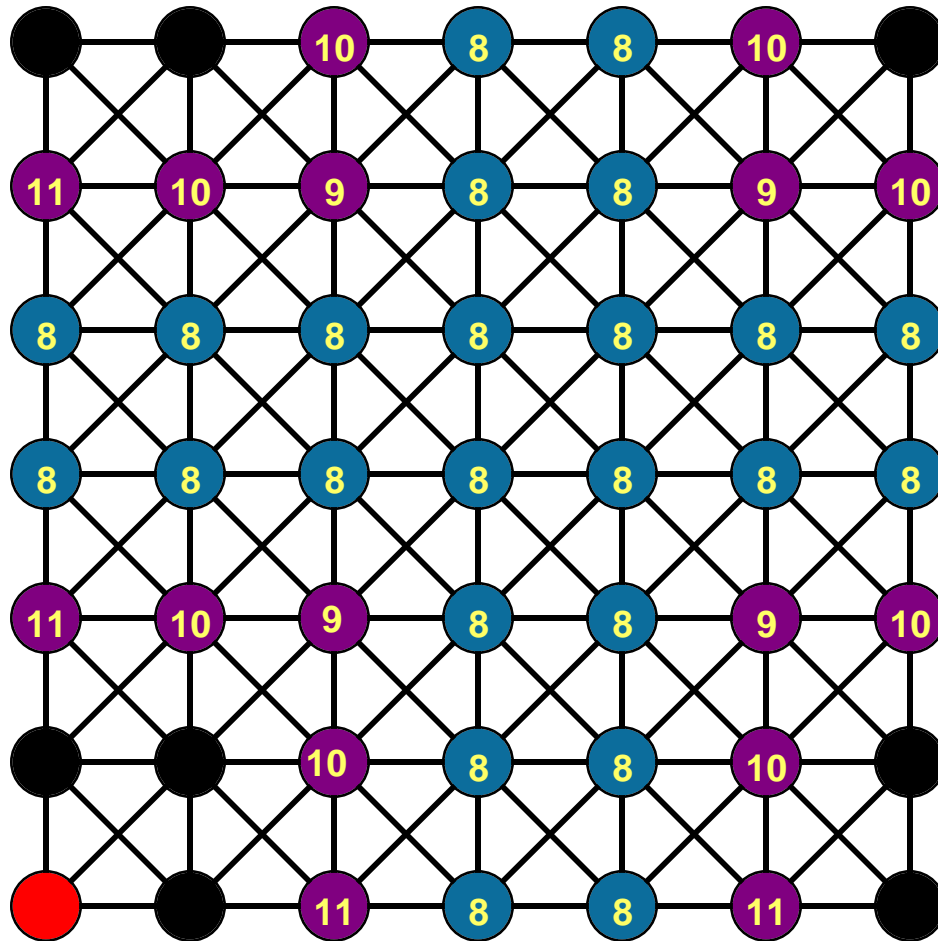
- **select C- pt with maximal measure**
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- **update measures of F- pt neighbors**

Coarse-grid selection: 9pt Laplacian, **periodic** boundary conditions



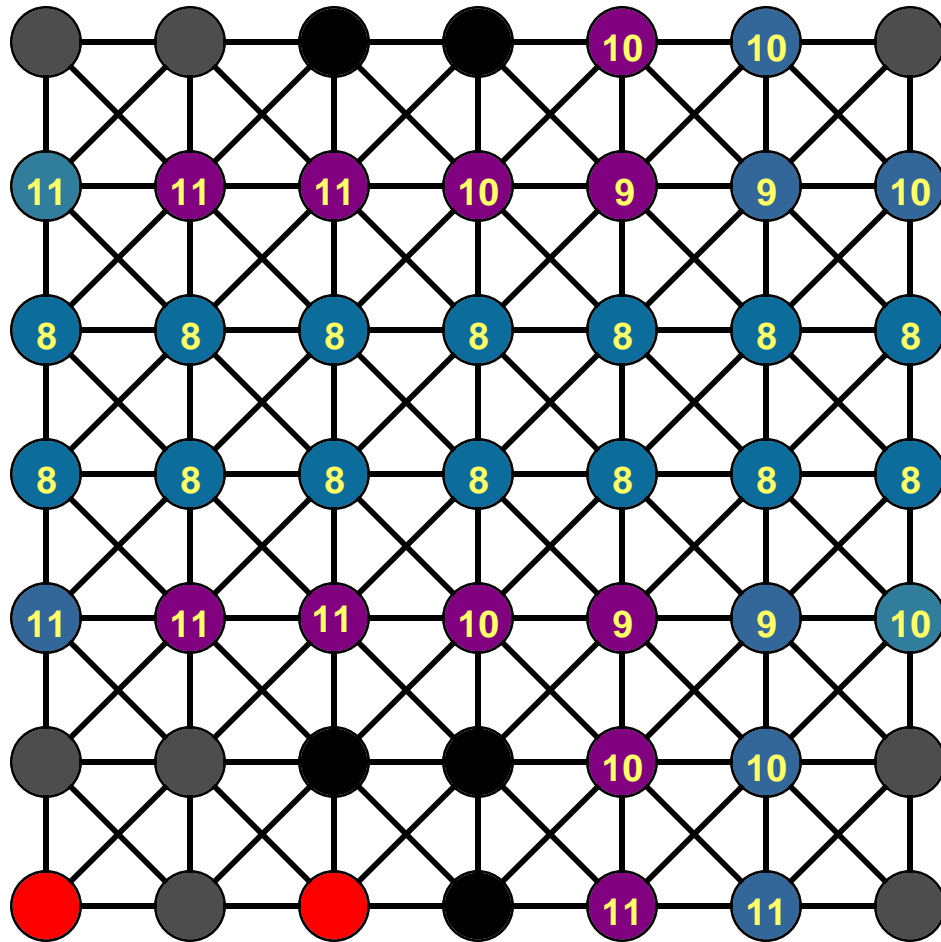
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Coarse-grid selection: 9pt Laplacian, **periodic** boundary conditions



- select C- pt with maximal measure
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- **update measures of F- pt neighbors**

Coarse- grid selection: 9pt Laplacian, **periodic** boundary conditions

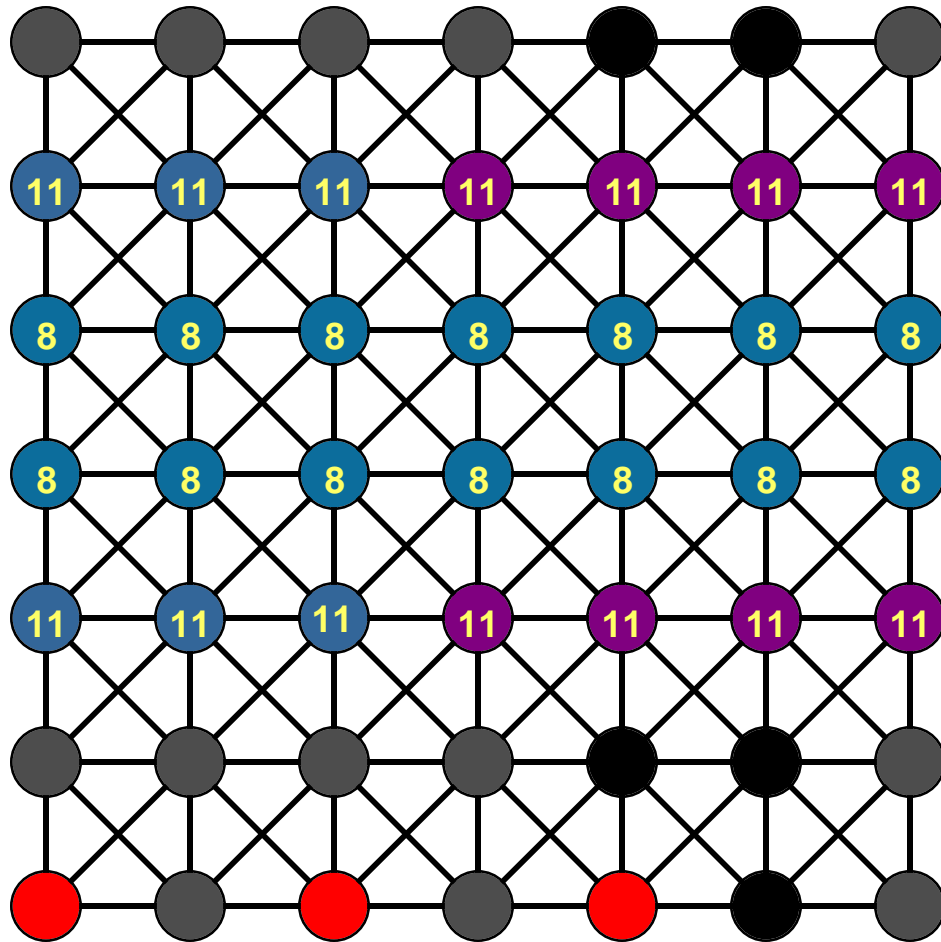


→ **select C- pt with maximal measure**

→ **select neighbors as F- pts**

→ **update measures of new F- pt neighbors**

Coarse-grid selection: 9pt Laplacian, **periodic** boundary conditions

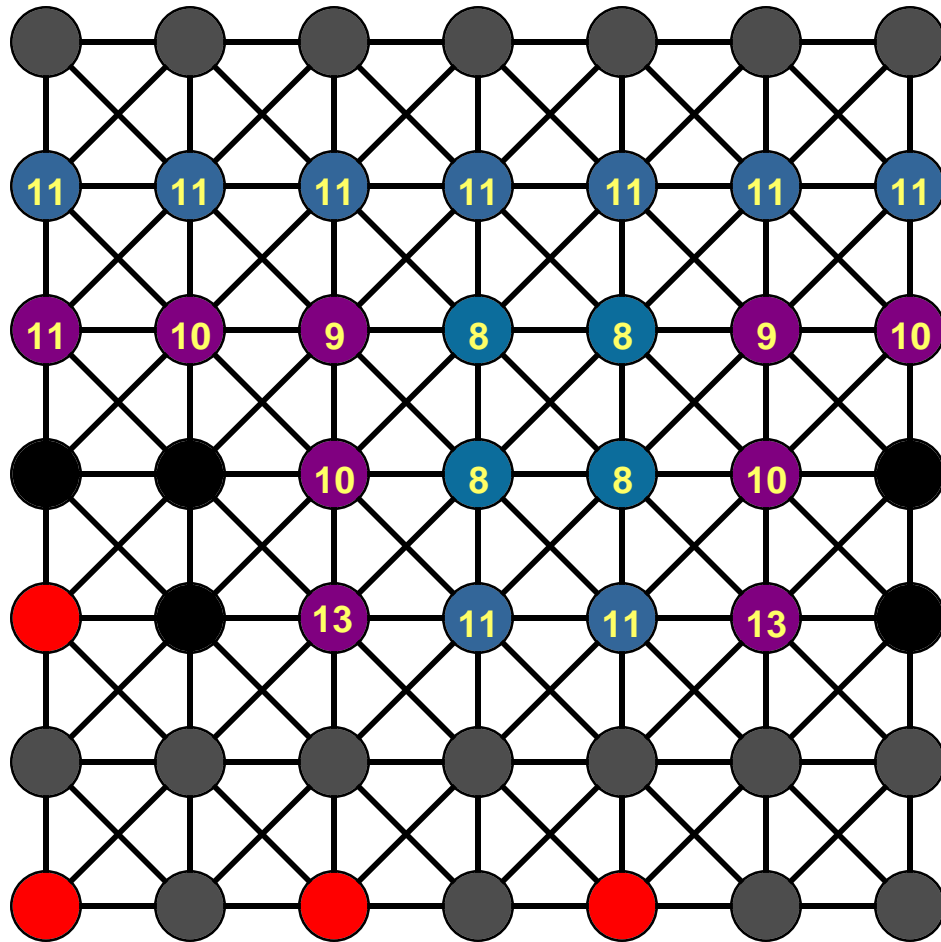


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Coarse-grid selection: 9pt Laplacian, **periodic** boundary conditions

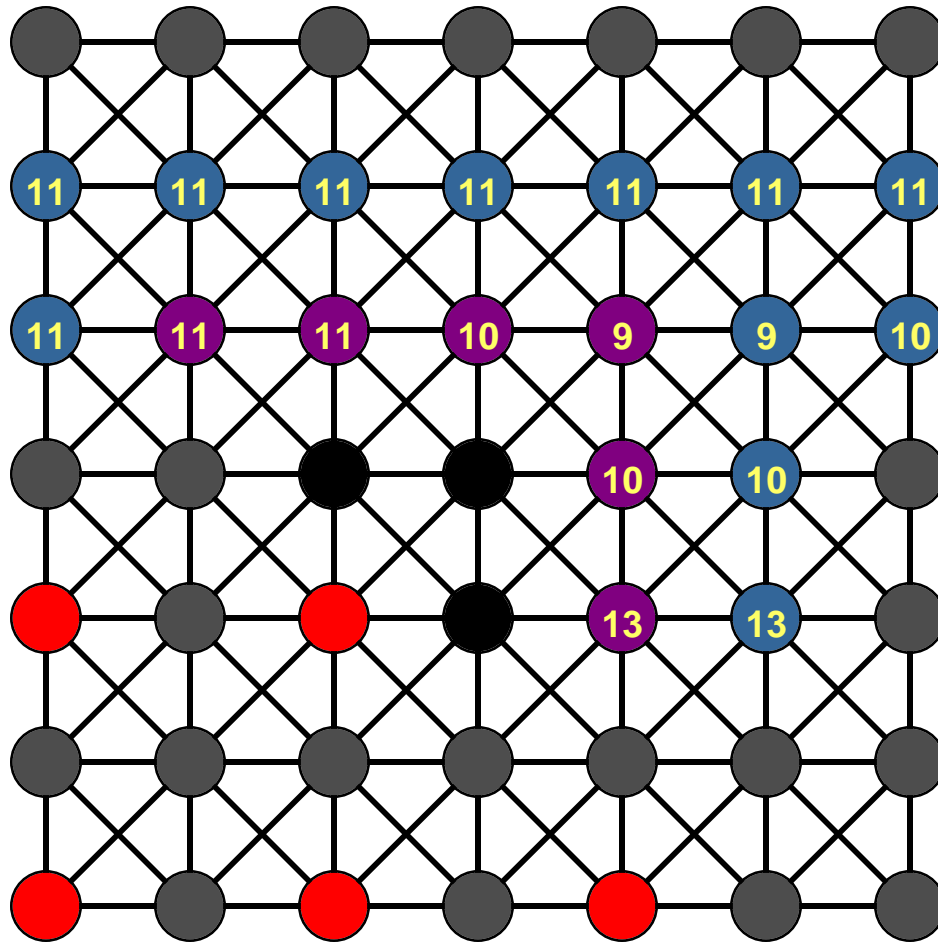


→ **select C- pt with maximal measure**

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Coarse- grid selection: 9pt Laplacian, **periodic** boundary conditions

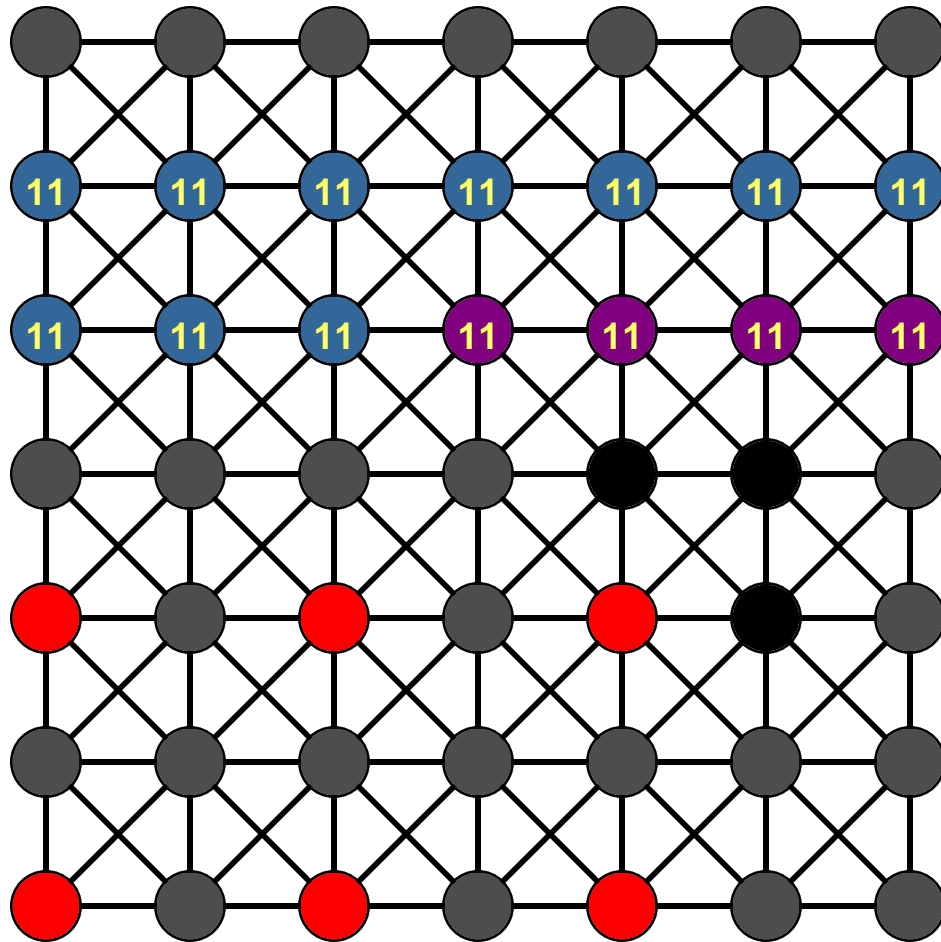


→ **select C- pt with maximal measure**

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Coarse-grid selection: 9pt Laplacian, **periodic** boundary conditions

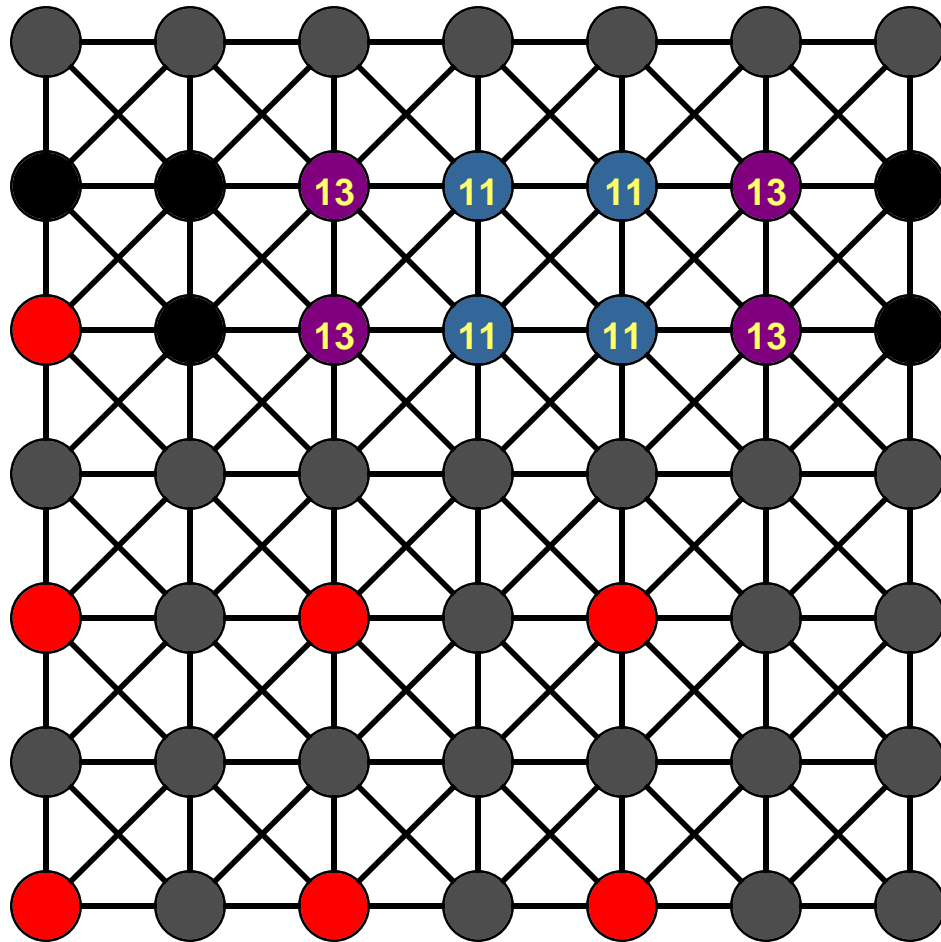


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Coarse-grid selection: 9pt Laplacian, **periodic** boundary conditions

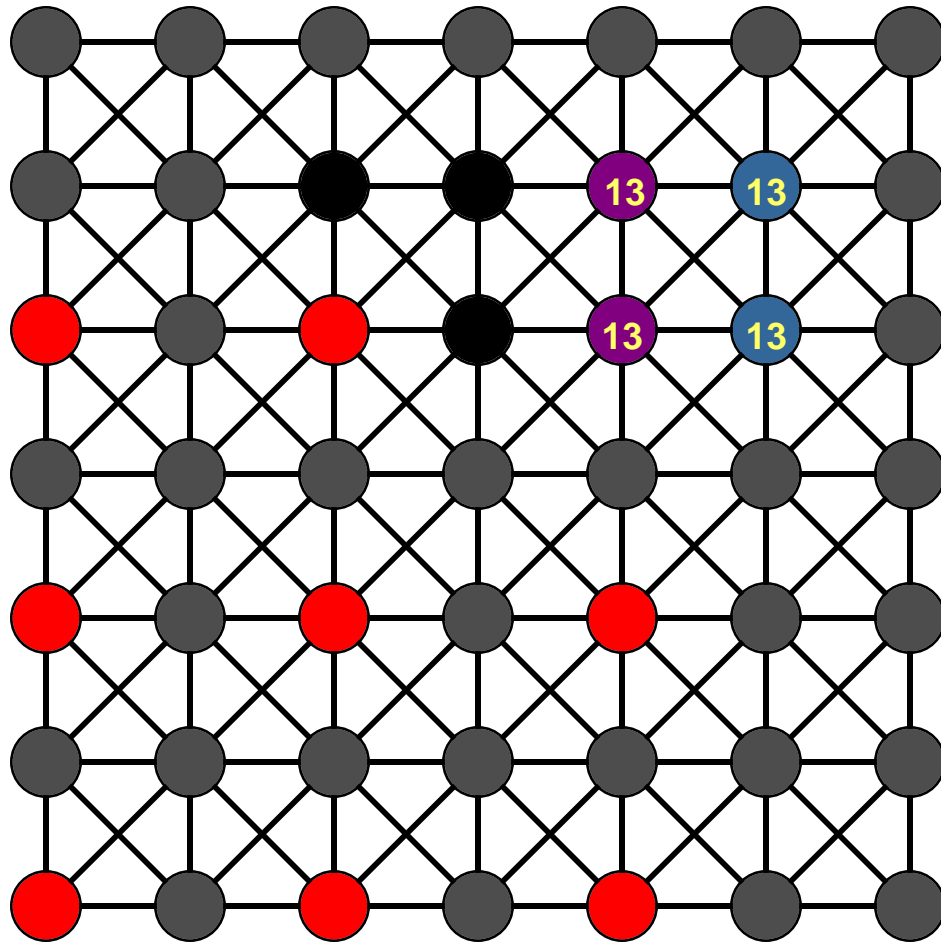


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→ **update measures of new F- pt neighbors**

Coarse-grid selection: 9pt Laplacian, **periodic** boundary conditions

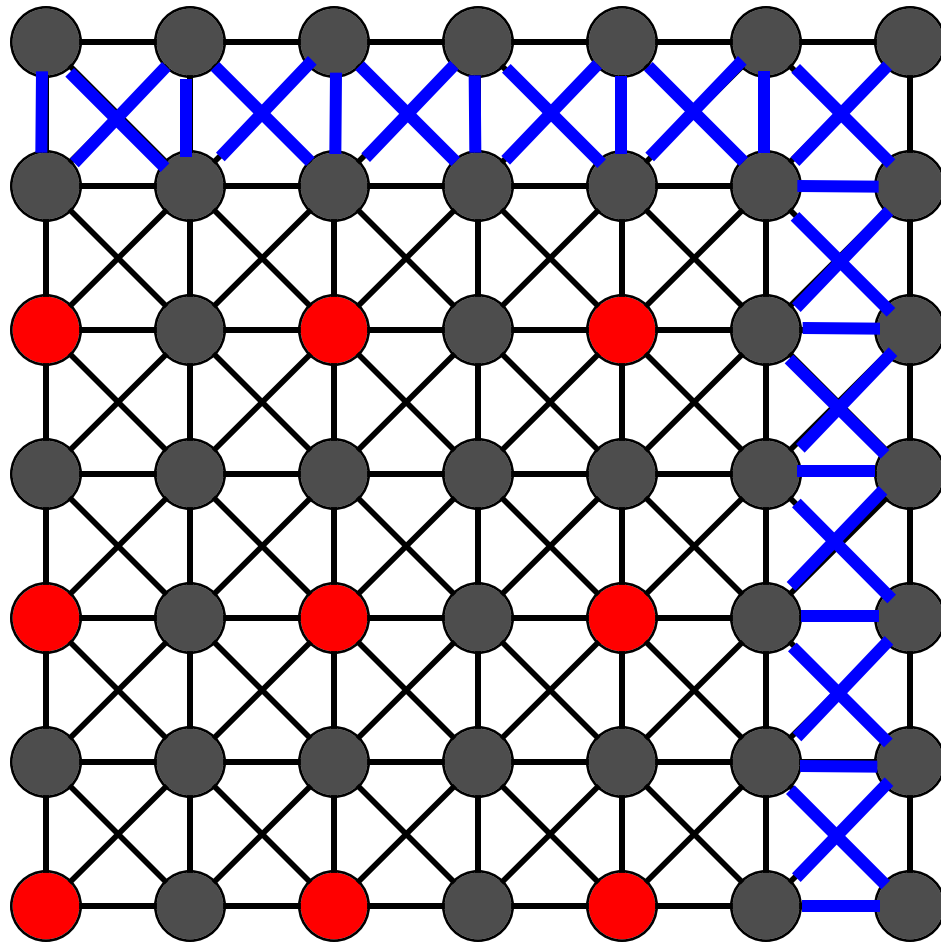


→ **select C- pt with maximal measure**

→ **select neighbors as F- pts**

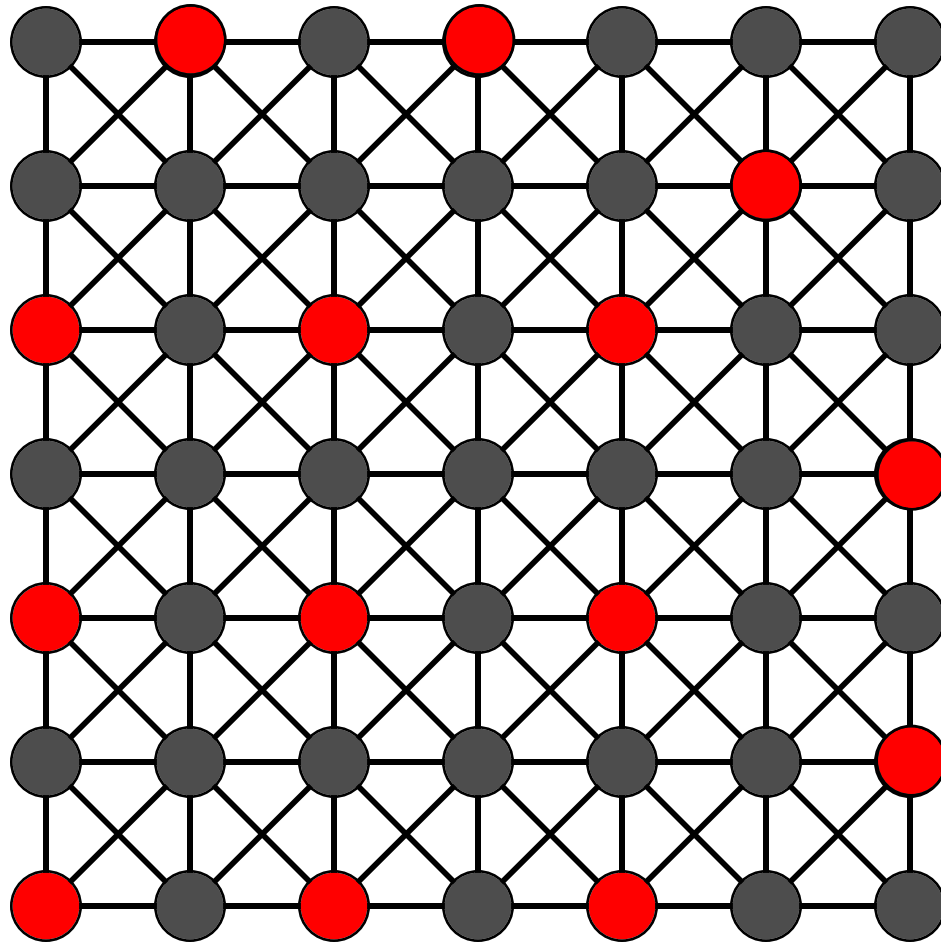
→ **update measures of new F- pt neighbors**

Coarse-grid selection: 9pt Laplacian, **periodic** boundary conditions



- ➔ **Modulo periodicity, it's the same coarsening as in the Dirichlet case.**
- ➔ **However, it has many F-F connections that do not share a common C-point**

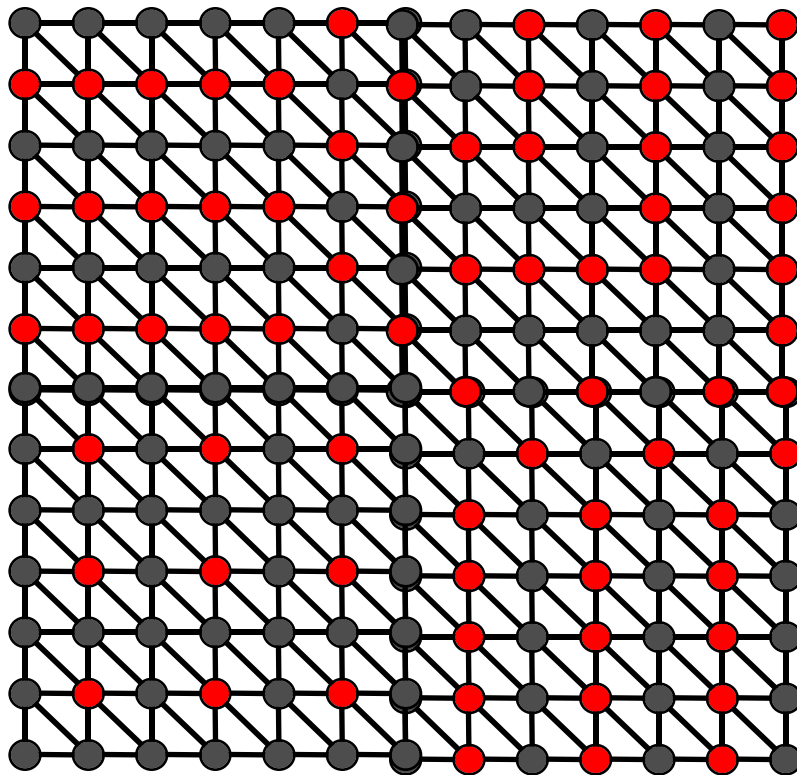
Coarse- grid selection: 9pt Laplacian, **periodic** boundary conditions



- A second pass is made in which some F- points are made into **C- points** to enforce (C1).
- Goals of the second pass include minimizing C- C connections, and minimizing the number of **C- points** converted to F- points.

How well does AMG coarsen:

$$-(a u_x)_x - (b u_y)_y + c u_{xy} = f(x, y)$$

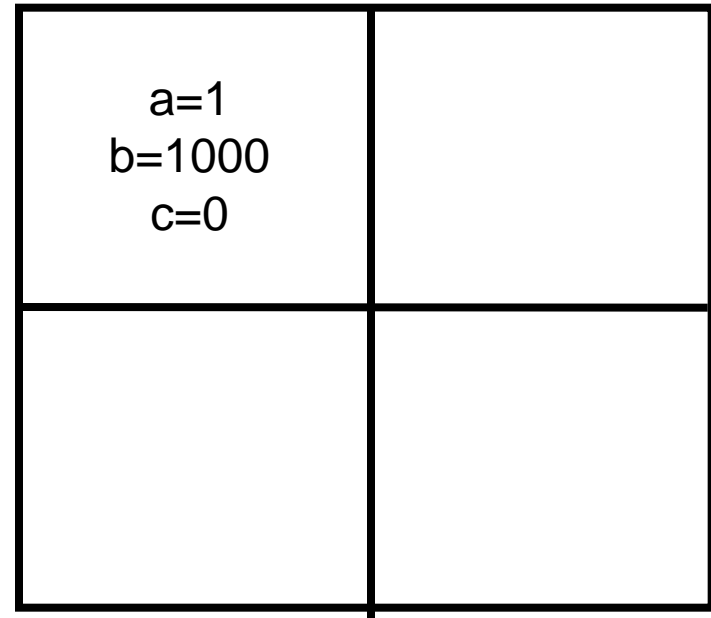
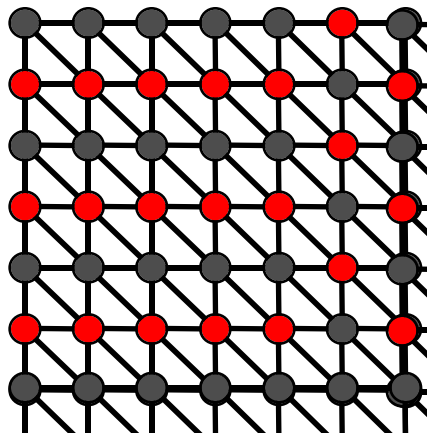


a=1 b=1000 c=0	A=1 b=1 c=2
a=1 b=1 c=0	a=1000 b=1 c=0

➡ In each region, AMG coarsens only in the direction of dependence!

How well does AMG coarsen:

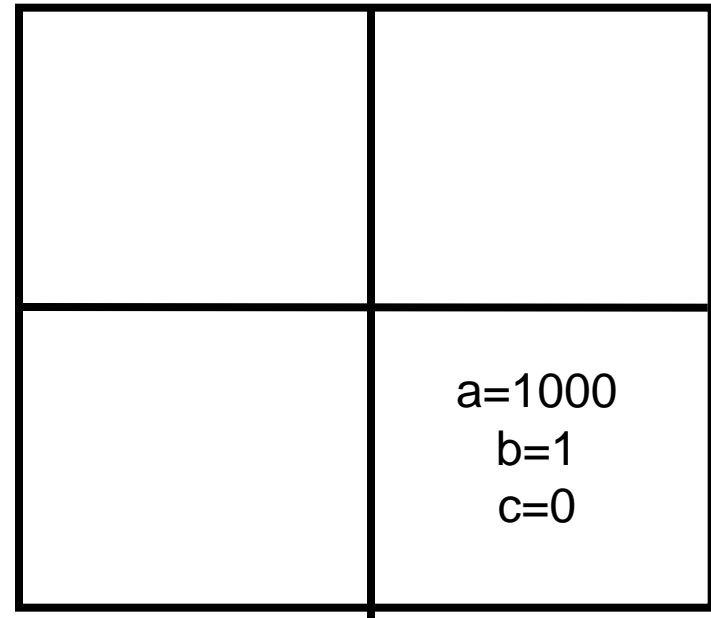
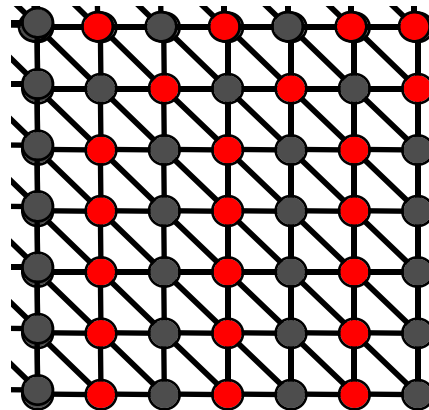
$$-(a u_x)_x - (b u_y)_y + c u_{xy} = f(x, y)$$



➡ In each region, AMG coarsens only in the direction of dependence!

How well does AMG coarsen:

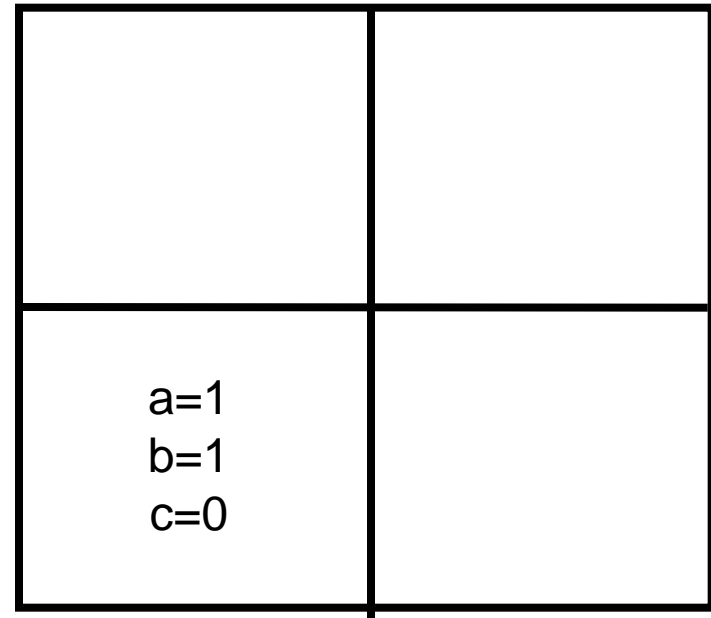
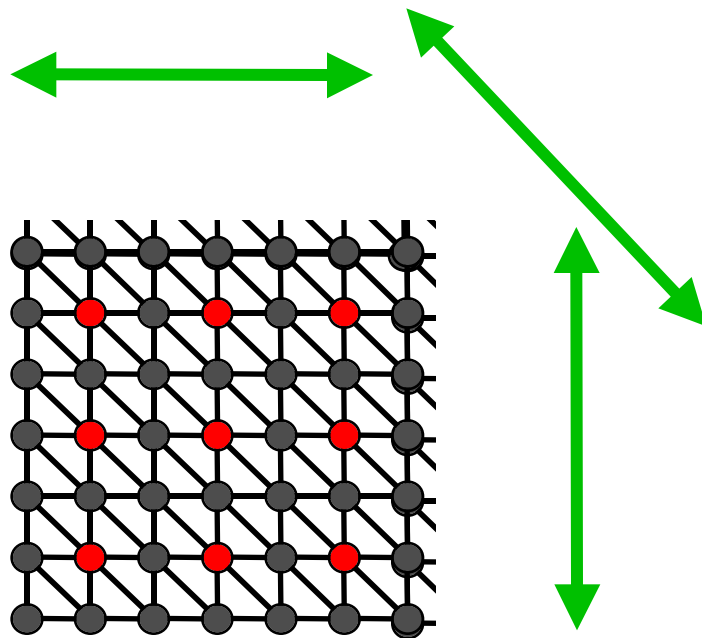
$$-(a u_x)_x - (b u_y)_y + c u_{xy} = f(x, y)$$



➔ In each region, AMG coarsens only in the direction of dependence!

How well does AMG coarsen:

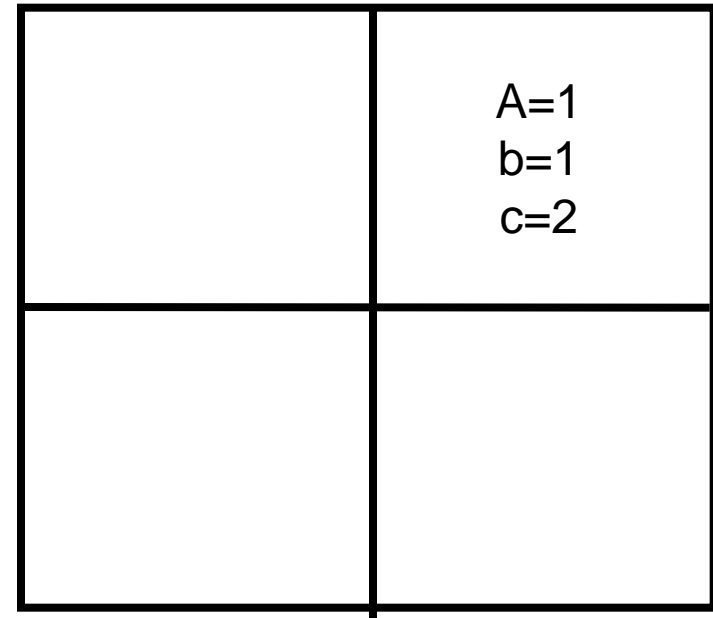
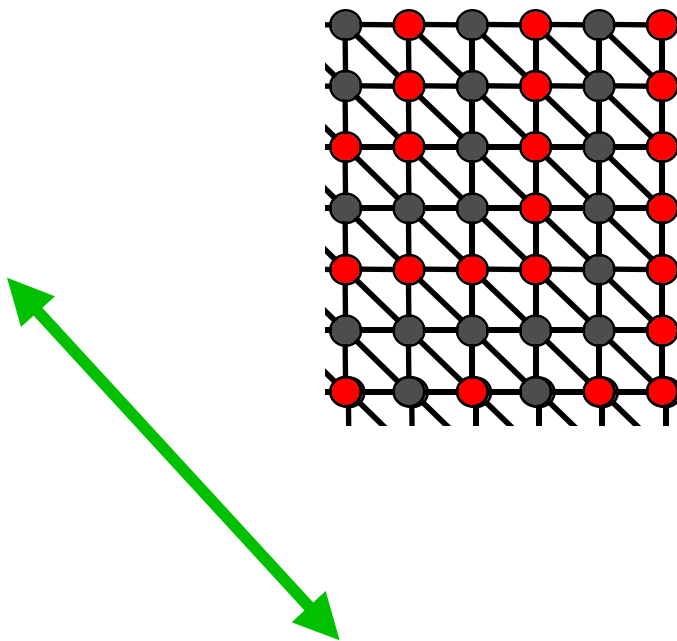
$$-(a u_x)_x - (b u_y)_y + c u_{xy} = f(x, y)$$



➔ In each region, AMG coarsens only in the direction of dependence!

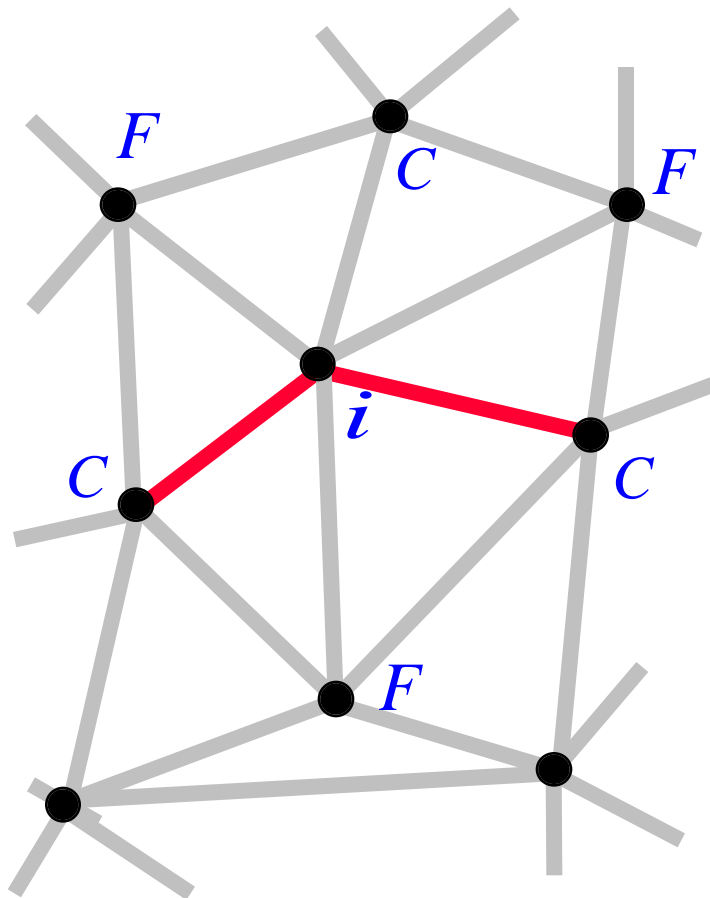
How well does AMG coarsen:

$$-(a u_x)_x - (b u_y)_y + c u_{xy} = f(x, y)$$



➔ In each region, AMG coarsens only in the direction of dependence!

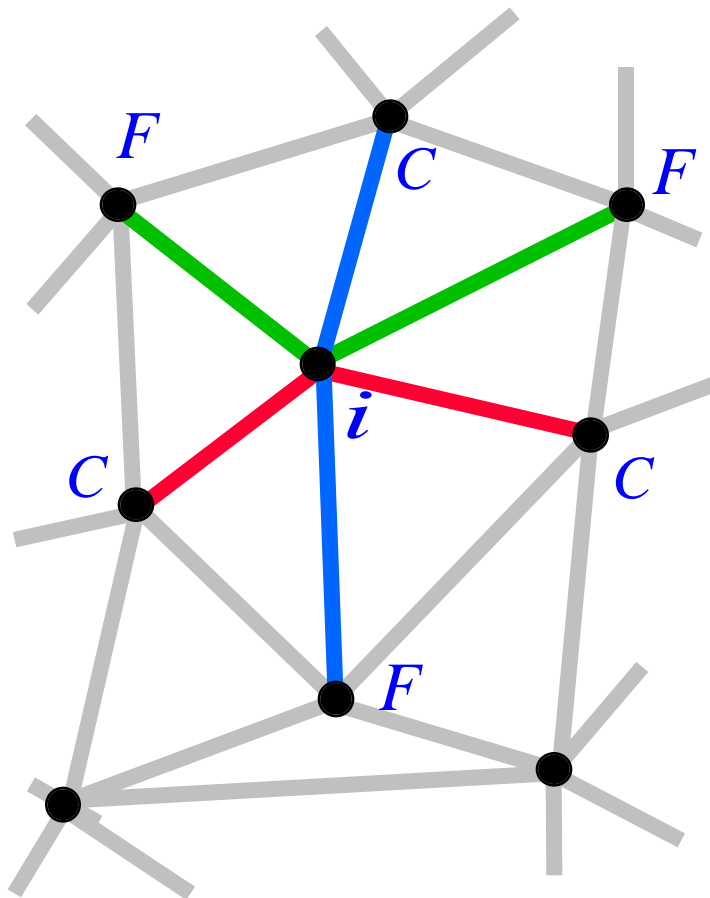
Prolongation



$$(Pe)_i = \begin{cases} e_i & , i \in C \\ \sum_{k \in C_i} w_{ik} e_k & , i \in F \end{cases}$$

The interpolated value at point i is just e_i if i is a C-point. If i is an F-point, the value is a weighted sum of the values of the points in the **coarse interpolatory set** C_i .

To define prolongation at i , we must examine the types of connections of u_i .



Sets of connection types:

C_i — i is dependent on these coarse interpolatory C-points.

D_i^S — i is dependent on these F-points.

D_i^W — i does not depend on these “weakly connected” points, which may be C- or F-

Prolongation is based on smooth error and dependencies (from M-matrices)

Recall that smooth error is characterized by “small” residuals:

$$r_i = a_{ii} e_i + \sum_{j \in N_i} a_{ij} e_j \quad 0$$

which we can rewrite as:

$$a_{ii} e_i = - \sum_{j \neq i} a_{ij} e_j$$

We base prolongation on this formula by “solving” for e_i and making some approximating substitutions.

Prolongation is based on smooth error and dependencies (from M-matrices)

We begin by writing the smooth-error relation:

$$a_{ii}e_i - \sum_{j \neq i} a_{ij}e_j$$

Identifying its component sums:

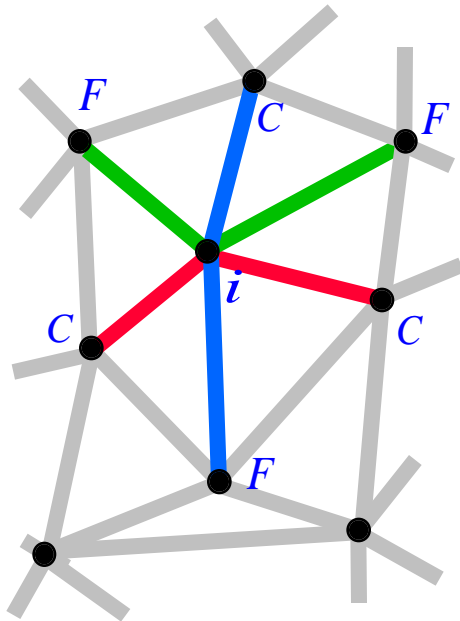
$$a_{ii}e_i - \sum_{j \in C_i} a_{ij}e_j - \sum_{j \in D_i^s} a_{ij}e_j - \sum_{j \in D_i^w} a_{ij}e_j$$

Coarse
interpolatory
set
F-point
dependencies
Weak
connections

We must approximate e_j in each of the last two sums in terms of e_i or of e_j for $j \in C_i$.

For the **weak connections**:

let $e_j = e_i$.



$$a_{ii}e_i - \sum_j C_i a_{ij}e_j - \sum_j D_i^s a_{ij}e_j - \sum_j D_i^w a_{ij}e_j$$

Coarse interpolatory set
F-point dependencies
Weak connections

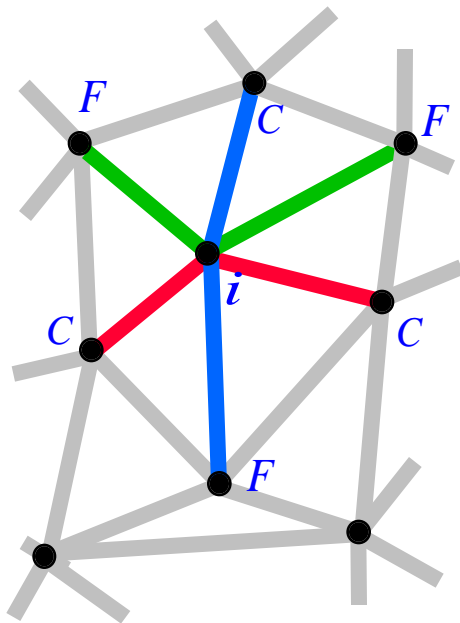
Effectively, this throws the weak connections onto the diagonal:

$$a_{ii} + \sum_j D_i^w a_{ij}e_i - \sum_j C_i a_{ij}e_j - \sum_j D_i^s a_{ij}e_j$$

This approximation can't hurt too much:

- Since the connection is weak,
- If i depended on points in D_i^w , smooth error varies slowly in the direction of dependence

For the **F-point dependencies**:
use a weighted avg. of errors in C_i C_j .



$$a_{ii} + \sum_j D_i^w a_{ij} e_i - \sum_j C_i a_{ij} e_j - \sum_j D_i^s a_{ij} e_j$$

Weak connections Coarse interpolatory set F-point dependencies

Approximate e_j by a weighted average of the e_k in the coarse interpolatory set

$$e_j = \frac{\sum_k C_i a_{jk} e_k}{\sum_k C_i a_{jk}}$$

It is for this reason that the intersection of the coarse interpolatory sets of two F-points with a dependence relationship must be nonempty **(C1)**.

Finally, the prolongation weights are defined

Making the previous substitution, and with a bit of messy algebra, the smooth error relation can be “solved” for e_i to yield the interpolation formula:

$$e_i = \sum_j C_{ij} e_j$$

where the prolongation weights are given:

$$C_{ij} = - \frac{a_{ij} + \frac{a_{ik}a_{kj}}{\sum_m D_{im}^s a_{km}}}{a_{ii} + \sum_n D_{in}^w}$$

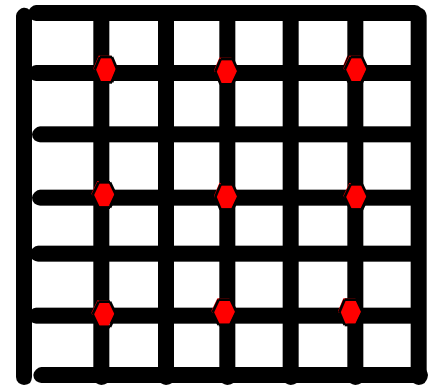
Highlights of Multigrid:

Storage: f^h, u^h must be stored each level

- In 1- d, each coarse grid has about half the number of points as the finer grid.



- In 2- d, each coarse grid has about one-fourth the number of points as the finer grid.



- In d- dimensions, each coarse grid has about 2^{-d} the number of points as the finer grid.

- Storage cost: $2N^d (1 + 2^{-d} + 2^{-2d} + 2^{-3d} + ? + 2^{-Md}) < \frac{2N^d}{1 - 2^{-d}}$

less than 2, 4/3, 8/7 the cost of storage on the fine grid for 1, 2, and 3- d problems, respectively.

AMG storage: grid complexity

- For AMG there is no simple predictor for total storage costs. u^m , f^m , and $A^m = I_{m-1}^m A^{m-1} I_{m-1}^m$ must be stored on all levels.
- Define γ , the **grid complexity**, as the total number of unknowns (gridpoints) on all levels, divided by the number of unknowns on the finest level. Total storage of the vectors u and f occupy 2γ storage locations.

AMG storage: operator complexity

- Define A , the **operator complexity**, as the total number of nonzero coefficients of all operators A^m divided by the number of nonzero coefficients in the fine-level operator A^0 . Total storage of the operators occupies A storage locations.

AMG storage: interpolation

- We could define I , an **interpolation complexity**, as the total number of nonzero coefficients of all operators I_m^{m+1} divided by the number of nonzero coefficients in the operator I_0^1 . This measure is not generally cited, however (like most multigridders, the AMG crowd tends to ignore the cost of intergrid transfers).
- Two measures that occasionally appear are A , the average “stencil size,” and I , the average number of interpolation points per F-point.

AMG Setup Costs: flops

- **Flops** in the setup phase are only a small portion of the work, which includes sorting, maintaining linked-lists, keeping counters, storage manipulation, and garbage collection.
- Estimates of the total flop count to define interpolation weights (I) and the coarse-grid operators (A) are:

$$A = N^I (2^I (A - I) + 3^I + A)$$

and

$$I = N^I (3(A - I) - 2)$$

AMG setup costs: a bad rap

- Many **geometric** MG methods need to compute prolongation and coarse-grid operators
- The only **additional** expense in the AMG setup phase is the coarse grid selection algorithm
- **AMG setup phase is only 10-25% more expensive than in geometric MG and may be considerably less than that!**

Highlights of Multigrid: Computation Costs

- Let 1 Work Unit (WU) be the cost of one relaxation sweep on the fine-grid.
- Ignore the cost of restriction and interpolation (typically about 20% of the total cost). (See?)
- Consider a V-cycle with 1 pre-Coarse-Grid correction relaxation sweep and 1 post-Coarse-Grid correction relaxation sweep.

- Cost of V-cycle (in WU):

$$2(1 + 2^{-d} + 2^{-2d} + 2^{-3d} + \dots + 2^{-Md}) < \frac{2}{1 - 2^{-d}}$$

- Cost is about 4, 8/3, 16/7 WU per V-cycle in 1, 2, and 3 dimensions.

AMG Solve Costs: flops per cycle

- The approximate number of flops in on level m for one relaxation sweep, residual transfer, and interpolation are (respectively)

$$2N_m^A \quad 2N_m^A + 2 \quad I N_m^F \quad N_m^C + 2 \quad I N_m^F$$

where N_m^A is the number of coefficients in A^m and N_m^C , N_m^F are the numbers of C-, F- points on m .

- The total flop count for a (ν_1, ν_2) V-cycle, noting that $N_m^F = N$ and letting $\nu = \nu_1 + \nu_2$ is approximately

$$N(2(\nu + 1)A + 4I + \nu - 1)$$

AMG Solve Costs: flops per cycle, again

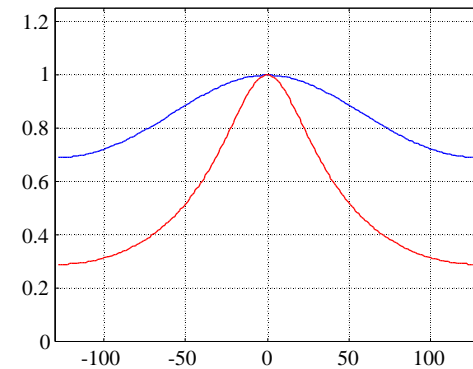
- All that is very well, but in practice we find the solve phase is generally dominated by the cost of relaxation and computing the residual.
- Both of those operations are proportional to the number of nonzero entries in the operator matrix on any given level.
- Thus the best measure of the ratio of work done on all levels to the work done on the finest level is operator complexity: A

Highlights of Multigrid: difficulties-anisotropic operators and grids

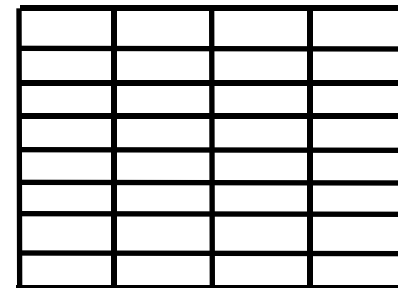
- Consider the operator :
$$-\frac{f_x^2 u}{f_x^2} - \frac{f_y^2 u}{f_y^2} = f(x, y)$$

- If $\epsilon_x \ll \epsilon_y$ then the GS-smoothing factors in the x - and y -directions are shown at right.

Note that GS relaxation does not damp oscillatory components in the x -direction.



- The same phenomenon occurs for grids with much larger spacing in one direction than the other:



Highlights of Multigrid: difficulties-discontinuous or anisotropic coefficients

- Consider the operator : $-(D(x, y) u)$ where

$$D(x, y) = \begin{pmatrix} d_{11}(x, y) & d_{12}(x, y) \\ d_{21}(x, y) & d_{22}(x, y) \end{pmatrix}$$

- Again, GS-smoothing factors in the x - and y -directions can be highly variable, and very often, GS relaxation does not damp oscillatory components in the one or both directions.
- Solutions: line-relaxation (where whole gridlines of values are found simultaneously), and/or semi-coarsening (coarsening only in the strongly coupled direction).

AMG does semi-coarsening automatically!

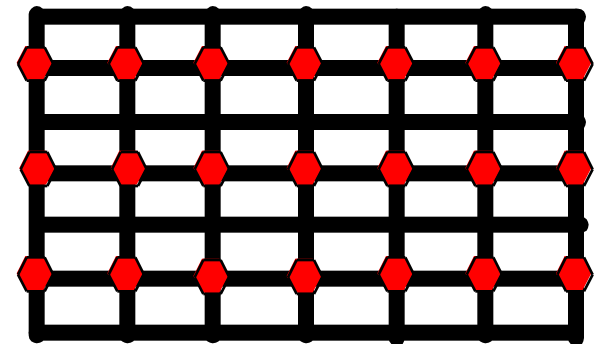
- Consider the operator :

$$-\frac{f^2 u}{f x^2} - \frac{f^2 u}{f y^2} = f(x, y)$$

- In the limit, as $\Delta x \times \Delta y$, the stencil becomes:

$$\begin{array}{ccc} -1 & -4 & -1 \\ 2 & 8 & 2 \\ -1 & -4 & -1 \end{array}$$

- AMG** automatically produces a semi-coarsened grid!!



AMG Convergence: there is theory (some)

- There is some theory, although it is of limited utility. It generally looks like:
- Theorem
 - Let $A^m \dots A$ be SPD, and let the interpolation operator I_{m+1}^m be full rank, and let restriction and coarse-grid operators be defined by
$$I_m^{m+1} = (I_{m+1}^m)^T \quad \text{and} \quad A^{m+1} = I_m^{m+1} A^m I_{m+1}^m$$
and let there be smoothing operators G^m and coarse-grid correction operators

$$T^m = I^m - I_{m+1}^m (A^{m+1})^{-1} I_m^{m+1} A^m$$

AMG Convergence: there is theory (some)

- Theorem (continued)

— suppose that, for all e^m ,

$$\|G^m e^m\|_A^2 \leq \|e^m\|_A^2 - \|T^m e^m\|_A^2$$

holds for some $\alpha > 0$ independently for all e^m and m .

Then $\alpha < 1$, and, provided the coarsest problem is solved and at least one smoothing step is performed after each coarse-grid correction step, the V-cycle has a convergence factor wrt the energy norm bounded above by

$$\sqrt{1 - \alpha}.$$

How's it perform (vol I)?

Regular grids, plain, old, vanilla problems

- The Laplace Operator:

	<i>Convergence</i>		<i>Time</i>	<i>Setup</i>
<i>Stencil</i>	<i>per cycle</i>	<i>Complexity</i>	<i>per Cycle</i>	<i>Times</i>
<i>5- pt</i>	<i>0.054</i>	<i>2.21</i>	<i>0.29</i>	<i>1.63</i>
<i>5- pt skew</i>	<i>0.067</i>	<i>2.12</i>	<i>0.27</i>	<i>1.52</i>
<i>9- pt (- 1, 8)</i>	<i>0.078</i>	<i>1.30</i>	<i>0.26</i>	<i>1.83</i>
<i>9- pt (- 1, - 4, 20)</i>	<i>0.109</i>	<i>1.30</i>	<i>0.26</i>	<i>1.83</i>

- Anisotropic Laplacian: $- U_{xx} - U_{yy}$

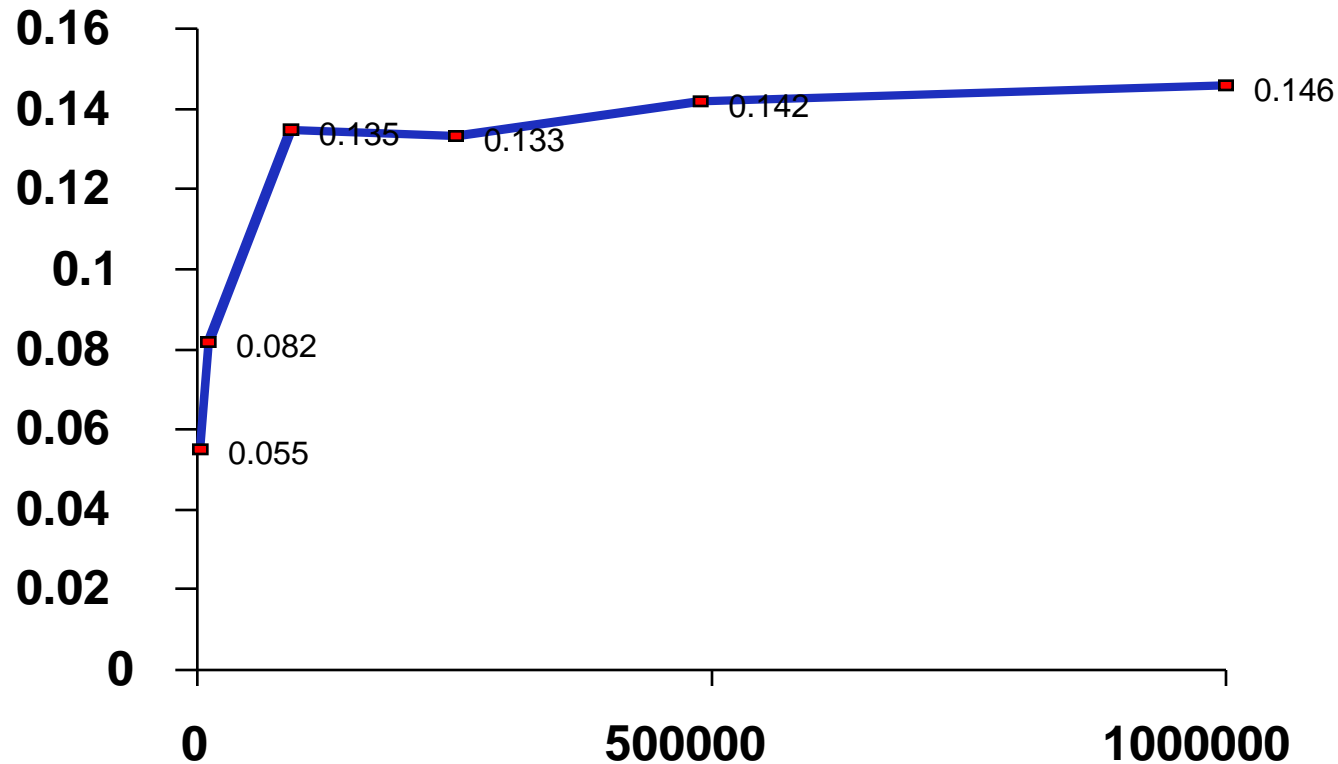
<i>Epsilon</i>	<i>0.001</i>	<i>0.01</i>	<i>0.1</i>	<i>0.5</i>	<i>1</i>	<i>2</i>	<i>10</i>	<i>100</i>	<i>1000</i>
<i>Convergence/cycle</i>	<i>0.084</i>	<i>0.093</i>	<i>0.058</i>	<i>0.069</i>	<i>0.056</i>	<i>0.079</i>	<i>0.087</i>	<i>0.093</i>	<i>0.083</i>

How's it perform (vol II)?

Structured Meshes, Rectangular Domains

- 5-point Laplacian on regular rectangular grids

Convergence factor (y- axis) plotted against number of nodes (x- axis)

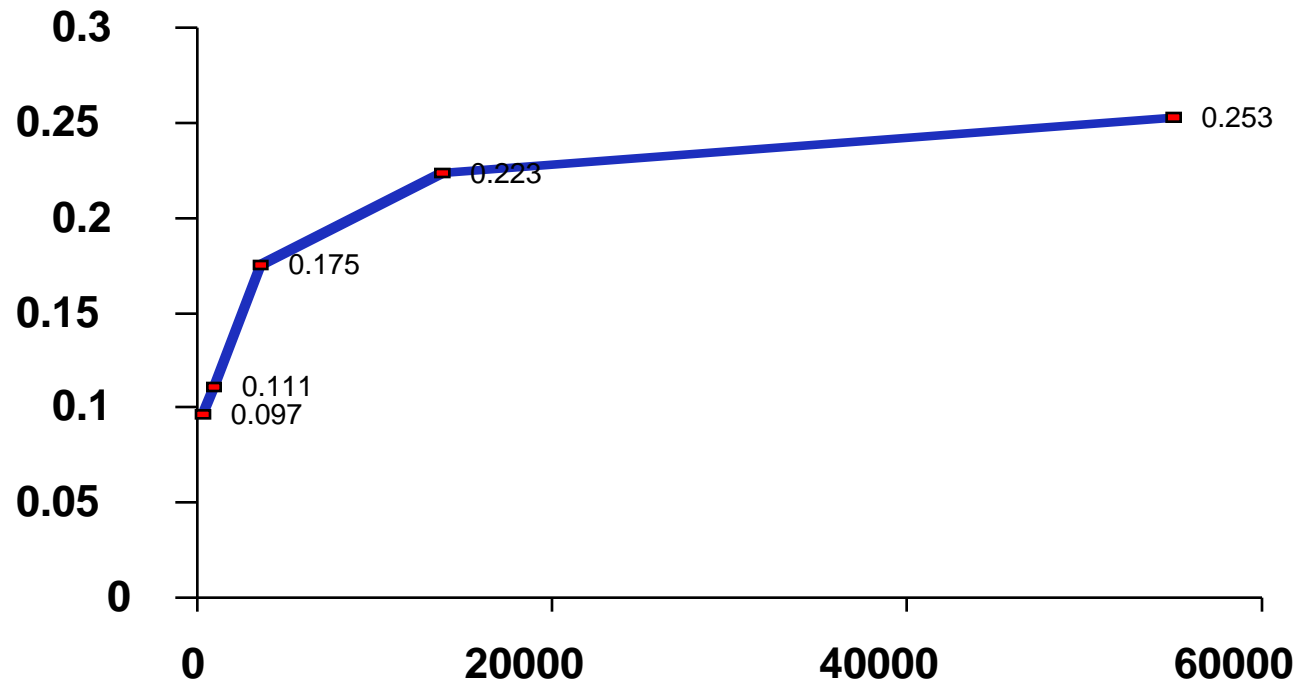


How's it perform (vol III)?

Unstructured Meshes, Rectangular Domains

- **Laplacian on random unstructured grids** (regular triangulations, 15- 20% nodes randomly collapsed into neighboring nodes)

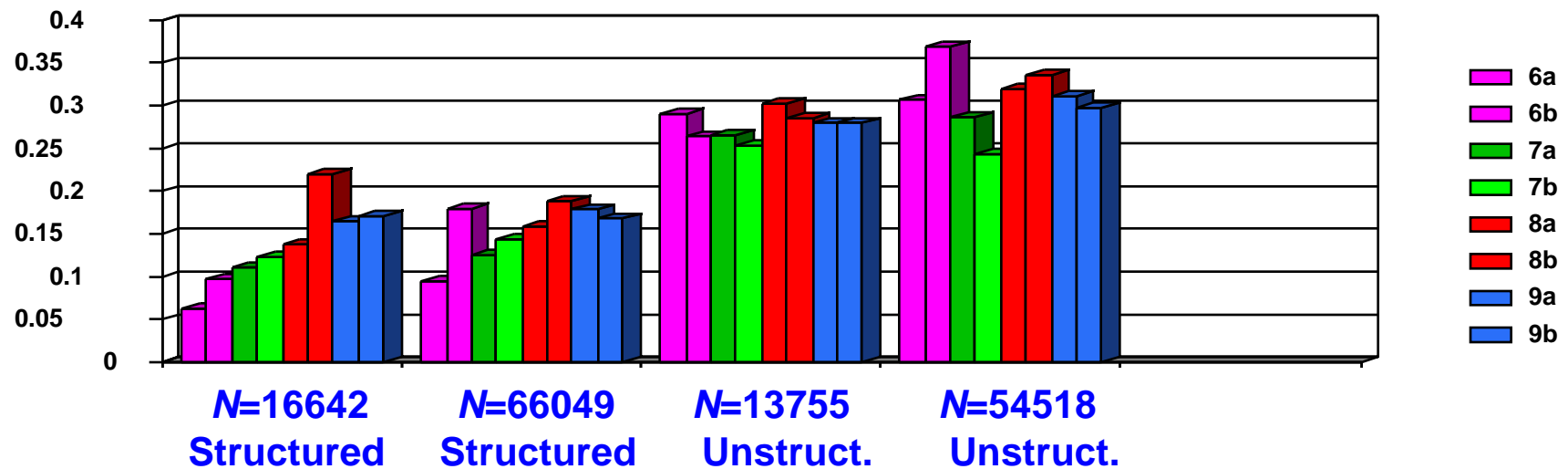
Convergence factor (y- axis) plotted against number of nodes (x- axis)



How's it perform (vol IV)?

Isotropic diffusion, Structured/Unstructured Grids

($d(x, y)$ u) on structured, unstructured grids



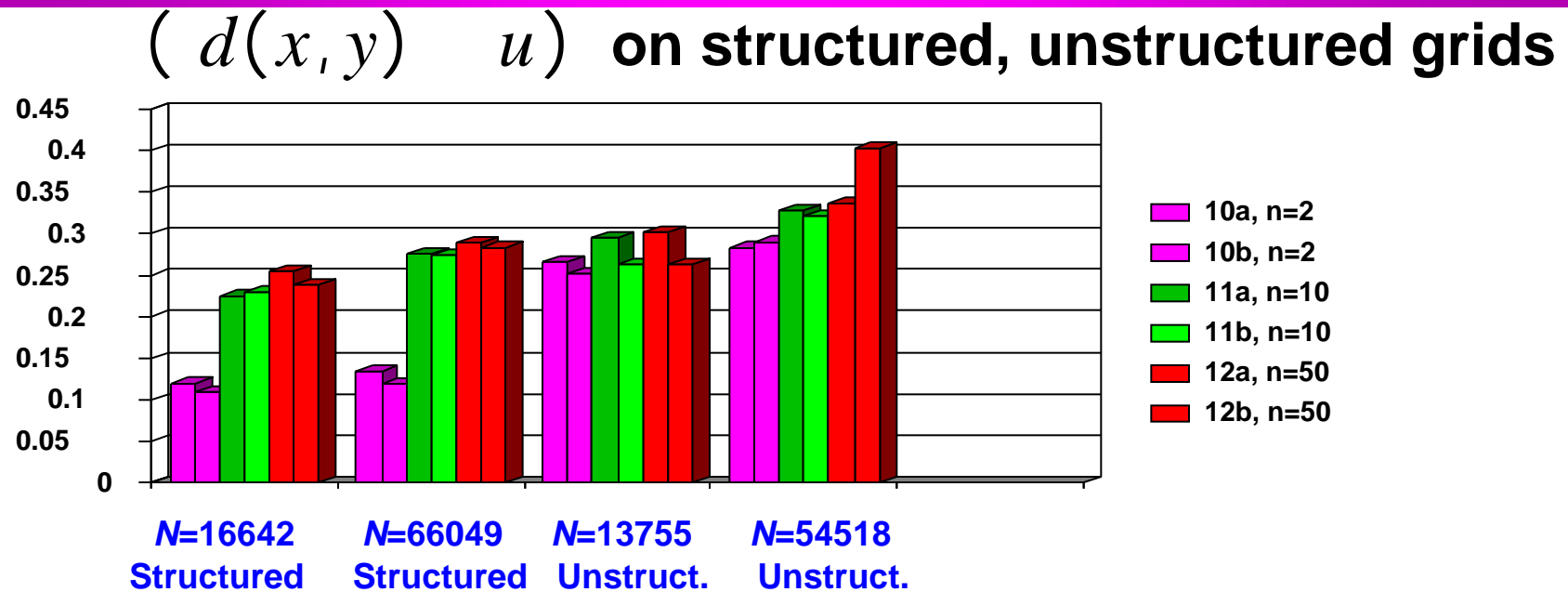
Problems used: “a” means parameter $c=10$, “b” means $c=1000$

$$6: d(x, y) = 1.0 + c |x - y| \quad 8: d(x, y) = \begin{matrix} 1.0 & 0.125 & \max\{|x-0.5|, |y-0.5|\} & 0.25 \\ c & & \text{otherwise} \end{matrix}$$

$$7: d(x, y) = \begin{matrix} 1.0 & x & 0.5 \\ c & x > 0.5 \end{matrix} \quad 9: d(x, y) = \begin{matrix} 1.0 & 0.125 & \sqrt{(x-0.5)^2 + (y-0.5)^2} & 0.25 \\ c & & \text{otherwise} \end{matrix}$$

How's it perform (vol IVa)?

Isotropic diffusion, Structured/Unstructured Grids



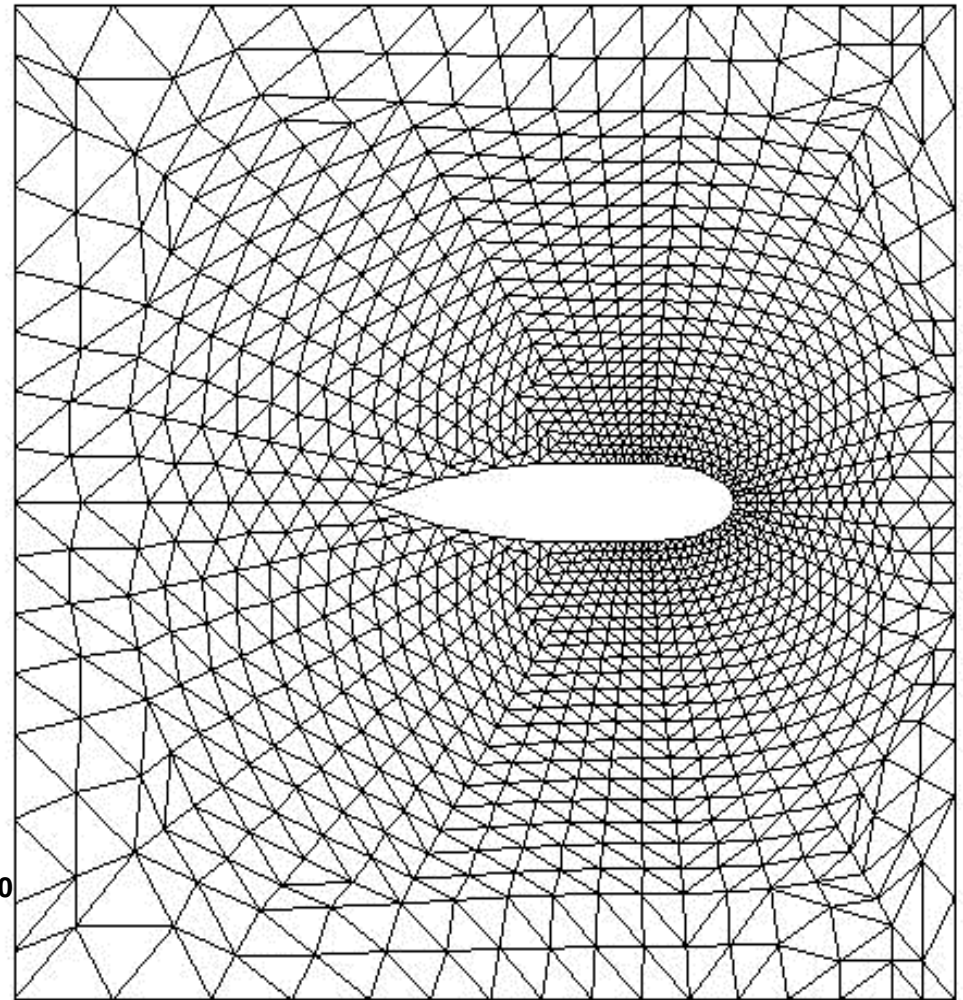
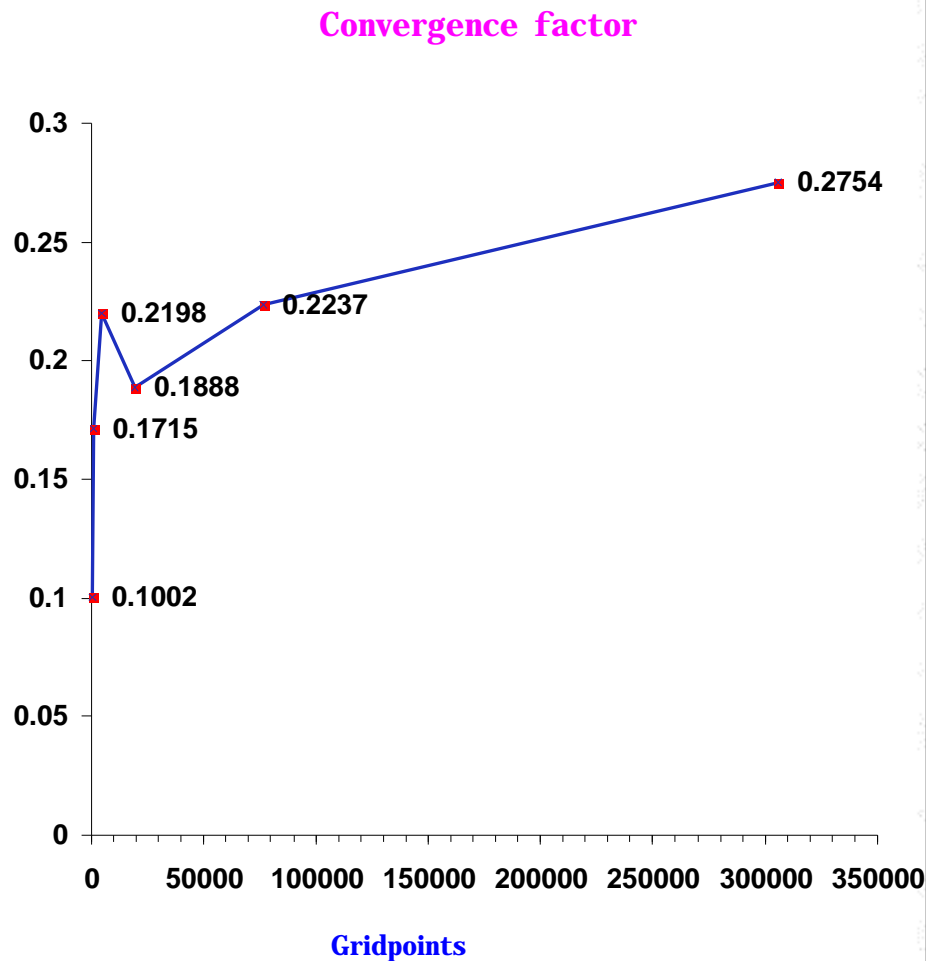
Problem used: “a” means parameter $c=10$, “b” means $c=1000$

“Checkerboard” of coefficients 1.0 and c , squares sized $1/n$:

$$d(x, y) = \begin{cases} 1.0 & \frac{i}{n} \leq x < \frac{i+1}{n}, \frac{j}{n} \leq y < \frac{j+1}{n}, i+j \text{ even} \\ c & \frac{i}{n} \leq x < \frac{i+1}{n}, \frac{j}{n} \leq y < \frac{j+1}{n}, i+j \text{ odd} \end{cases}$$

How's it perform (vol V)?

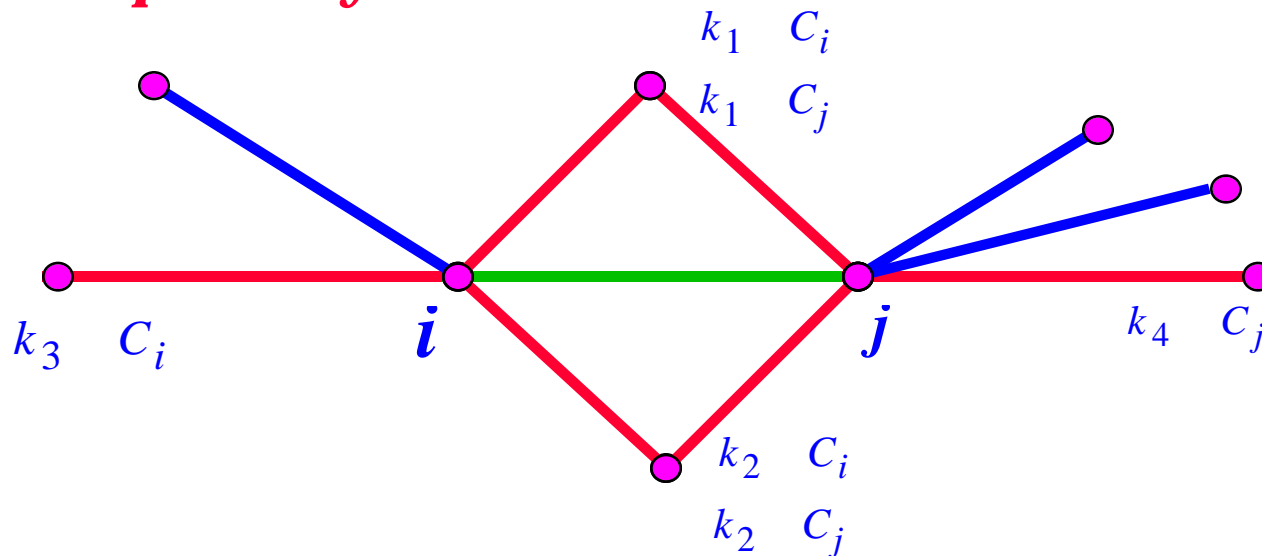
Laplacian operator, unstructured Grids



So, what could go wrong?

Strong F-F connections: weights are dependent on each other

- For point i the value e_j is interpolated from k_1, k_2 , and is needed to make the interpolation weights for approximating e_i .
- For point j the value e_i is interpolated from k_1, k_2 , and is needed to make the interpolation weights for approximating e_j .
- *It's an implicit system!*



Is there a fix?

- A Gauss-Seidel like **iterative** approach to weight definition is implemented. Usually two passes suffice. But does it work?

- Frequently, it does:

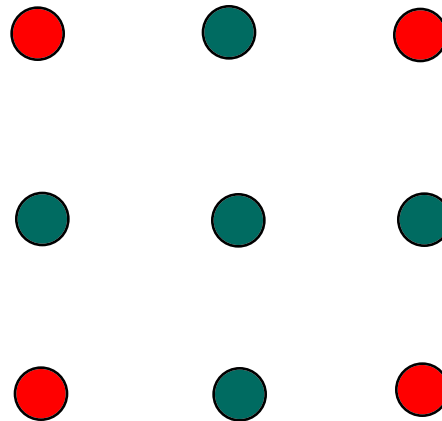
Convergence factors for

Laplacian, stretched quadrilaterals

	<i>theta</i>	<i>Standard</i>	<i>Iterative</i>
$x = 10 \quad y$	0.25	0.47	0.14
	0.5	0.24	0.14
$x = 100 \quad y$	0.25	0.83	0.82
	0.5	0.53	0.23

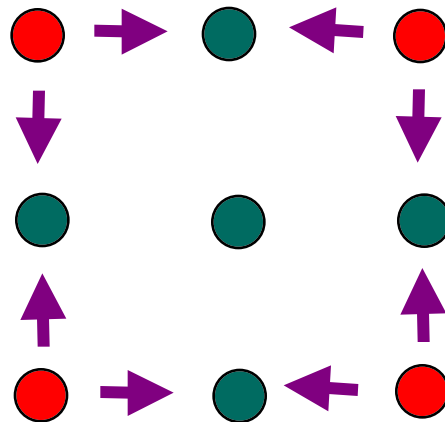
Another Fix: indirect interpolation (see Stueben's text for detail)

- The 5-point problem cannot give “full” coarsening because the **F-point** in the middle has no connection to any of the 4 **C-points**. Hence, there is no way to interpolate its value.



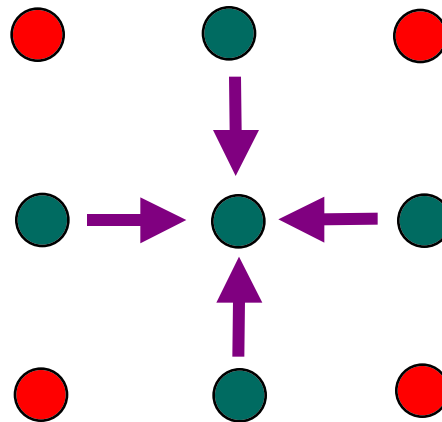
Another Fix: indirect interpolation (see Stueben's text for detail)

- Full coarsening could be achieved by indirect interpolation.
- First interpolate the **F- points** from the **C- points**.



Another Fix: indirect interpolation (see Stueben's text for detail)

- Full coarsening could be achieved by indirect interpolation.
- First interpolate the **F- points** from the **C- points**.
- Then interpolate the “middle” from the **F- points**.



- Similar treatment could be applied whenever F- F dependencies arise.

AMG for systems

- How can we do AMG on systems?

$$\begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} f \\ g \end{pmatrix}$$

- **Naïve** approach: “Block” approach (block Gauss-Seidel, using scalar AMG to “solve” at each cycle)

$$\begin{aligned} u &= (A_{11})^{-1} (f - A_{12} v) \\ v &= (A_{22})^{-1} (g - A_{21} u) \end{aligned}$$

- **Great Idea! Except that it doesn't work!** (relaxation does not evenly smooth errors in both unknowns)

AMG for systems: a solution

- To solve the system problem, allow interaction between the unknowns at all levels:

$$A^k = \begin{pmatrix} A_{11}^k & A_{12}^k \\ A_{21}^k & A_{22}^k \end{pmatrix} \quad \text{and} \quad I_{k+1}^k = \begin{pmatrix} (I_{k+1}^k)_u & 0 \\ 0 & (I_{k+1}^k)_v \end{pmatrix}$$

- This is called the “unknown” approach.
- Results: 2- D elasticity, uniform quadrilateral mesh:

<i>mesh spacing</i>	0.125	0.0625	0.03135	0.01562
<i>Convergence factor</i>	0.22	0.35	0.42	0.44

So, what **else** can go wrong?

Ouch! Thin body elasticity!

- Elasticity, 3- d, thin bodies!

$$u_{xx} + \frac{1-}{2} (u_{yy} + u_{zz}) + \frac{1+}{2} (v_{xy} + w_{xz}) = f_1$$

$$v_{yy} + \frac{1-}{2} (v_{xx} + v_{zz}) + \frac{1+}{2} (u_{xy} + w_{yz}) = f_2$$

$$w_{zz} + \frac{1-}{2} (w_{xx} + w_{yy}) + \frac{1+}{2} (u_{xz} + v_{yz}) = f_3$$

- Slide surfaces, Lagrange multipliers, force balance constraints:

$$\begin{matrix} S & T & x_1 \\ U & V & x_2 \end{matrix} = \begin{matrix} F_1 \\ F_2 \end{matrix}$$

- **S** is “generally” positive definite, **V** can be zero, $U^T ? T$.

Wanted:

**Good solution
method
for this
problem.**

REWARD

Needed: more robust methods for **characterizing** smooth error

- Consider quadrilateral finite elements on a stretched 2D Cartesian grid ($dx \rightarrow \infty$):

$$A = \begin{bmatrix} -1 & -4 & -1 \\ 2 & 8 & 2 \\ -1 & -4 & -1 \end{bmatrix}$$

- Direction of dependence is not apparent here
- **Iterative weight interpolation** will sometimes compensate for mis-identified dependence
- Elasticity problems are still problematic

Scalability is central for large-scale parallel computing

- A code is **scalable** if it can **effectively** use additional computational resources to solve larger problems
- Many specific factors contribute to scalability:
 - architecture of the parallel computer
 - parallel implementation of the algorithms
 - **convergence rates of iterative linear solvers**

Linear solver convergence can be discussed independent of parallel computing, and is often overlooked as a key scalability issue.

In Conclusion, AMG Rules!

- Interest in AMG methods is high, and probably still rising, because of the increasing importance of terra-scale simulations on unstructured grids.
- *AMG has been shown to be a robust, efficient solver on a wide variety of problems of real-world interest.*
- *Much research is underway to find effective ways of parallelizing AMG, which is essential to large-scale computing.*

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